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Research Paper

Relationship Between Segment Disclosure and the Accuracy of Earnings Forecasts in Brazil

Júlia Alves e Souza[1], Douglas José Mendonça[2], Gideon Carvalho de Benedicto[3], Francisval de Melo Carvalho[4]
[1](*Universidade Federal Fluminense)*
[2,3,4](*Universidade Federal de Lavras)*
[1]*Corresponding Author*

ABSTRACT: *This study investigates the relationship between the extent of segment disclosure by Brazilian publicly traded companies and the accuracy of earnings forecasts issued by investment analysts. The sample comprises 94 listed firms, and the analysis covers the period from 2010 to 2017. Segment disclosure was identified through a content analysis of the explanatory notes accompanying the financial statements. The degree of segment disclosure was quantified using Item Response Theory (IRT), while forecast accuracy was measured based on the consensus of analysts' earnings per share (EPS) forecasts. Panel data regression models were estimated using the Random Effects approach with robust standard errors. The findings reveal considerable variation in the level of segment disclosure across firms, reflecting the discretionary nature of managerial reporting practices. The main empirical result indicates that the extent of segment disclosure is not significantly associated with the accuracy of analysts' earnings forecasts. Although segment reporting aims to enhance transparency by detailing the nature and financial effects of a company's operations and the economic environments in which it operates, the evidence suggests that greater disclosure does not necessarily lead to more accurate assessments of firms' earnings potential. These results support the argument that certain features of segment reporting may constrain its informational usefulness for external users.*

KEYWORDS: *Segment information, Accounting disclosure, Earnings forecasts, Financial analysis.*

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I. INTRODUCTION

Most of the information presented in the financial statements of publicly traded companies is reported in aggregate form – that is, at the company level – without disaggregation by the individual components that constitute the organization. However, many companies operate across multiple business segments, which are defined as the distinct operational units that make up a company's overall activity (Garrison et al., 2013). The disclosure of solely aggregated accounting data hinders the identification and analysis of the specific characteristics and financial performance of these individual segments.

André, Filip and Moldovan (2016) emphasize that operating segments can differ substantially in terms of profitability, risk exposure and expected returns. In the case of diversified firms, assessing the impact of individual segments on overall performance becomes increasingly complex. Subunits of a single company may operate in different industries, each with distinct revenue profiles and profit trajectories. Since the company's overall performance reflects the combined outcomes of its various segments, a lack of disaggregated information limits users' ability to evaluate the associated risks, benefits and future prospects of the business (Benjamin et al., 2010).

In recognition of the limitations posed by aggregated reporting, many jurisdictions have established regulatory requirements mandating the disclosure of financial information by operating segment. These regulations aim to enhance the transparency and decision-usefulness of financial statements, particularly for investors and analysts who rely on detailed segment-level information to assess firm performance and make informed forecasts.

Building on the premise that the aggregation of financial information can impede effective performance evaluation, many countries have mandated the disclosure of segment-specific data. In Brazil, such a requirement was implemented in 2009, obligating publicly traded companies to report segment information in their financial statements. This mandate was established through Pronunciamento Contábil CPC 22 – Informação por segmento, which aligns with International Financial Reporting Standard (IFRS) 8 – Operating Segments. Consequently, Brazilian companies began reporting segment-level data for fiscal years ending in 2010 and beyond. Following the global adoption of IFRS 8, the issue of segment reporting has gained increasing academic and regulatory relevance, particularly in emerging markets such as Brazil.

The core rationale for mandating segment disclosure lies in the informational value it offers to users, particularly in enhancing the quality of financial analysis. Segment reporting enables the identification of critical attributes such as the company's managerial structure, the most relevant regions of operation, product lines, high-performing segments and the profit margins associated with each activity (Schirivic, 2014). Accordingly, such disclosures are expected to support and improve the analytical work of investment analysts.

According to Martinez (2004), forecasting is among the most essential tasks performed by analysts. To generate reliable forecasts, these professionals must rely not only on mandatory and voluntary corporate disclosures but also on sectoral and macroeconomic indicators. One of the key metrics used to evaluate the quality of analysts' forecasts is accuracy (Gatsios, 2013; Pessotti, 2012; Pessanha, 2012; Cotter, Tarca, & Wee, 2012; Dumer, 2012). Forecast accuracy refers to the degree to which predictions align with actual outcomes; thus, more accurate forecasts are considered to be of higher quality (Martinez, 2004).

Given the increased transparency provided by segment disclosures, it is reasonable to expect an improvement in earnings forecast accuracy. However, limitations related to the quality and presentation of such disclosures may prevent these expected benefits from materializing. Several concerns have been raised regarding the reporting framework established by IFRS 8, which was adopted in Brazil. Although segment reporting is widely regarded as a key component in investment analysis, deficiencies in how companies disclose segment information can limit its utility in the forecasting process.

The international literature presents divergent views on the relationship between segment disclosure and the accuracy of earnings forecasts. Some studies suggest a positive association, where greater segment transparency leads to improved forecast accuracy (Berger & Hann, 2003; Kajüter & Nienhaus, 2017). In contrast, other research finds no significant relationship between the two variables (André, Filip, & Moldovan, 2016; He et al., 2016). As such, there is no clear consensus in the literature, highlighting the need for further empirical investigation to deepen understanding of this relationship.

In light of the foregoing, this study aims to investigate the relationship between the level of segment disclosure among Brazilian firms and the accuracy of earnings forecasts issued by investment analysts. Specifically, it seeks to determine whether forecast accuracy varies according to the degree of segment information disclosed by these companies.

This research contributes to the fields of Accounting and Finance by offering some of the first empirical evidence on the usefulness of segment information in the Brazilian context. Such an investigation is essential for enhancing the understanding of the potential impact of segment reporting on the use of financial statements. According to Kang and Gray (2014), segment disclosure has received considerable international attention as one of the ongoing challenges in financial reporting. Nichols et al. (2013) further highlight that the usefulness of segment information remains a subject of global inquiry, with empirical findings differing across institutional and economic contexts. This study seeks to explore, in an original and context-specific manner, the relationship between segment reporting and analysts' forecast accuracy in Brazil.

The article is organized into five sections. Following this introduction, Section 2 presents the theoretical framework underpinning the study. Section 3 outlines the methodological procedures adopted. Section 4 reports and discusses the empirical results. Finally, Section 5 provides concluding remarks and reflections on the study's contributions.

II. LITERATURE REVIEW

2.1 Segment Reporting from the Perspective of Agency Theory and Value Relevance Studies

A key justification for segment reporting is its role in mitigating information asymmetry between corporate managers and external users of financial statements. This rationale is grounded in Agency Theory, a framework used to analyze relationships in systems where ownership and control of capital are distributed among different individuals (Segatto-Mendes, 2001).

Jensen and Meckling (1976) are recognized as foundational contributors to Agency Theory. According to them, an agency relationship exists when one party (the principal) engages another (the agent) to perform services on their behalf, thereby delegating decision-making authority to the agent. The authors emphasize that the agent may not always act in the best interests of the principal, due to conflicting incentives and goals.

Agency Theory assumes the existence of information asymmetry, whereby one party possesses more or better information than the other. In the principal-agent relationship, this typically means that the agent holds privileged information that significantly influences the outcomes of their decisions (Jensen & Meckling, 1976).

As Segatto-Mendes (2001) notes, the majority of information received by the principal originates from the agent, who controls not only the content but also the depth of the information disclosed—creating asymmetry that can undermine the efficiency of capital markets.

Kudlawicz-Franco et al. (2016) further observe that information asymmetry is a persistent feature of many markets, often arising from the cost or difficulty of acquiring accurate information. Moreover, asymmetry may be linked to stock return volatility, as investors make decisions with incomplete data influenced by multiple external and internal factors.

Within this context, segment disclosure is viewed as a key mechanism for reducing information asymmetry (Joliet & Muller, 2016; Cho, 2015; Schirivic, 2014). By reporting disaggregated financial data by segment, companies offer external users insight into the same operational information used by internal management for decision-making. As a result, shareholders (the principals) gain access to relevant information that was previously available only to company executives (the agents).

However, Agency Theory also suggests that managers, acting in their own self-interest, may withhold or selectively disclose information. Bens et al. (2011) identify agency costs as a primary factor influencing the level and quality of segment disclosures. In practice, managers may choose not to disclose detailed information about segments that are critical to internal decision-making (Weschenfelder & Mazzioni, 2014).

Therefore, enhanced transparency through segment-level disclosure can help to alleviate agency conflicts in capital markets, potentially improving investment efficiency (Cho, 2015). Bushman and Smith (2001) argue that reducing information asymmetry lowers the likelihood of suboptimal investment decisions and assists investors in more effectively allocating resources across available market options.

Despite expectations that capital markets respond to financial statement disclosures, questions persist regarding the informational adequacy of these statements. This concern stems from either insufficient disclosure or limitations in the accounting measurement methodologies employed. The Value Relevance literature addresses this issue by investigating the degree to which accounting information correlates with stock prices (Barth et al., 2001).

Barth et al. (2001) propose that the Value Relevance approach is based on the premise that accounting figures significantly influence investor decisions by shaping market perceptions. According to this view, stock prices reflect a consensus of investor expectations, which is in turn influenced by the accounting information disclosed. Consequently, accounting values serve as tools for forecasting performance and evaluating firm value. Gatsios (2013) highlights an additional contribution of this research stream: it enables the evaluation of the impact of changes in accounting standards by examining their effects on capital market behavior, thereby offering a means of assessing the quality and usefulness of disclosed information.

The disclosure of accounting information by companies tends to influence their market valuation. According to Lambert et al. (2007), the quality of accounting disclosure affects market participants' perceptions of future cash flows. Consequently, the level of disclosure can shape expectations and influence the process of valuing a company's equity, thereby affecting its market value.

From the perspective of the Value Relevance approach, an important question is whether the disclosure of operating segment information has an impact on firm valuation. If such information possesses informational content for external users, its disclosure should be reflected in the company's share price. Studies such as Joliet and Muller (2016) have highlighted the relevance of segment disclosures, emphasizing their usefulness within capital markets. However, as noted by Santos et al. (2018), when segment disclosure is incomplete or of poor quality, it may fail to provide meaningful input for users' decision-making processes, thus limiting its relevance and utility.

2.2 Earnings Forecasts Made by Analysts

Investment analysts are professionals who evaluate the performance and future prospects of companies, with a particular focus on their profit-generating capacity. According to Domingues and Nakao (2016), the primary objective of analysts is to formulate earnings forecasts to support recommendations regarding the purchase, sale, or retention of stocks.

An essential aspect of analysts' work involves forecasting corporate earnings. Forecasting plays a central role in investment evaluation and significantly influences market expectations, which in turn affect stock prices. As noted by Dalmácio et al. (2013), reliable projections of future earnings are critical for accurately assessing a stock's fair value. To conduct such evaluations, analysts typically undertake a rigorous process that includes understanding the company's business environment, analyzing available data, constructing valuation models and making informed recommendations (Dalmácio, 2009; Martinez, 2004).

Market participants place considerable value on analysts' forecasts. These professionals are expected to apply their expertise and analytical tools to estimate company performance and issue reports disseminated through financial information systems. These reports serve as important inputs for other professionals and investors in making investment decisions (Lima, 2015). The quality of these analyses is instrumental in guiding actions that aim to maximize investment returns.

Nevertheless, analysts face limitations in consistently producing forecasts that closely align with actual outcomes. While accurate information provided by analysts can enhance the functioning of capital markets, inaccurate or biased forecasts can undermine investor confidence. Martinez (2004) points out that systematic limitations or inefficiencies in analysts' forecasts may mislead investors and compromise the credibility of financial markets. Consequently, as emphasized by Dalmácio et al. (2013), evaluating the quality of analysts' forecasts is essential for investors to understand the reliability and limitations of the information available to them.

According to Dumer (2012), most studies on analysts' projections focus on estimates of earnings per share (EPS), which are then compared to the actual EPS reported by companies. Notably, publicly traded companies widely disclose their actual EPS, making it a consistent benchmark. Domingues and Nakao (2016) explain that empirical studies typically assess the difference between analysts' EPS forecasts and the actual reported EPS, providing insight into forecast performance.

When the actual EPS differs from the forecasted EPS, a forecasting error is observed. The degree of this error is commonly evaluated using the metric of accuracy, which measures how closely the forecast aligns with the actual outcome (Gatsios, 2013; Pessotti, 2012; Pessanha, 2012; Cotter et al., 2012; Dumer, 2012; Dalmácio, 2009; Martinez, 2004). Higher accuracy reflects greater forecasting quality and analyst effectiveness in predicting corporate profits.

Dalmácio (2009) categorizes analysts' recommendations into: strong buy and buy (when a company's estimated value is below its current market price); hold (when estimated and market values are aligned); and sell or strong sell (when the estimated value exceeds the market price). These recommendations, based on analysts' projections, can significantly influence investor behavior.

Forecasts may also exhibit bias. An optimistic bias occurs when the forecasted EPS exceeds the actual earnings, whereas a pessimistic bias is observed when the forecast is lower than the actual earnings. In the latter case, the company outperformed the analyst's expectations. Several studies suggest that analysts often exhibit a systematic optimistic bias in their forecasts, projecting earnings higher than those ultimately reported (Dechow & Schrand, 2004; Martinez, 2004).

In evaluating earnings forecasts—whether in terms of accuracy or bias—researchers may consider either individual analyst forecasts or aggregated forecasts. According to Martinez (2004), the literature is generally divided into two streams: one focusing on individual analysts' forecasts and recommendations and the other examining consensus forecasts. The consensus is typically calculated as the average or median of all analysts' EPS forecasts for a particular company in a given period and is widely interpreted as a proxy for market expectations. As such, it serves as a valuable reference point for investors when making decisions.

2.3 Factors That May Influence the Accuracy of Earnings Forecasts Made by Investment Analysts

Given the importance of earnings forecasts to capital markets, several studies have investigated the factors that may influence their accuracy. According to Gatsios (2013), one stream of research focuses on the determinants of individual analysts' estimates. In this context, the accuracy of each forecast is examined in light of specific characteristics of the analysts. These characteristics include the analyst's individual experience, sector specialization, the number of firms under coverage, the frequency of forecast issuance and features of the brokerage firms where these analysts are employed (Dalmácio et al., 2013; Dalmácio, 2009; Martinez, 2004).

A second stream of research addresses the determinants of consensus forecasts, typically measured by the median or average of analysts' earnings projections, representing the market's collective expectation for a company's performance. The primary variables analyzed in this line of research include company-specific characteristics, attributes of the analysts, industry-related factors and the broader institutional environment in which financial information is disclosed (Silva, 2015; Gatsios, 2013; Dalmácio et al., 2013; Pessotti, 2012; Glaum et al., 2011; Hodgdon et al., 2008; Hussain, 1997; Lang & Lundholm, 1996).

Table 1 provides a summary of some of the key factors identified in the literature as potential determinants of earnings forecast accuracy.

Table 1 - Description of the factors that influence the accuracy of analysts' earnings forecasts

Factor	Description	Relationship	Authors
Number of Analysts	Number of analysts following the company	The larger the number of analysts following the company, the higher the forecast accuracy	Dalmácio et al. (2013), Glaum et al. (2011), Hodgdon et al. (2008), Lang & Lundholm (1996)

Loss occurrence	Binary variable indicating whether the company made a loss in the year	Forecast accuracy is lower when the company makes a loss	Dalmácio (2009), Behn, Choi & Kang (2008)
Company size	Measured by total revenue, total assets or market value of the company	The larger the company, the greater the accuracy of the forecast	Glaum et al. (2011), Hodgdon et al. (2008), Martinez (2004), Lang e Lundholm (1996)
Indebtedness	Ratio of third-party capital to the company's total assets	The higher the company's debt, the lower the accuracy the forecasts	Glaum et al. (2011)
Profit volatility	Percentage change in profit from one year to the next	The greater the volatility in the company's results, the lower the accuracy of the forecast	Glaum et al. (2011), Hodgdon et al. (2008), Hussain (1997)
Profitability	Return on assets (net profit divided by total assets) of the company	The higher the company's profitability, the greater the accuracy of the forecast	Glaum et al. (2011)
Particularities of each year	Variables representing each year analyzed	Economic circumstances and political factors that occurred in each year influence the accuracy of analysts' forecasts	Behn et al. (2008)
Corporate governance	The company must be listed in one of the corporate governance from B3	Forecasts are more accurate for companies that adopt differentiated corporate governance practices	Dalmácio et al. (2013), Dalmácio (2009)
Optimistic bias	Binary variable representing whether the value predicted was higher than real value	Forecast accuracy is higher when there is an optimistic bias (expected value higher than actual)	Behn et al. (2008)
Sector of activity	Segregation of firms by sector of activity	Forecasts are more accurate for companies in certain sectors than others	Glaum et al. (2011), Hodgdon et al. (2008), Hussain (1997)

Thus, a wide array of characteristics may affect the precision of analysts' earnings forecasts. Silva (2015) and Lima (2015) point out that, while research on this topic is relatively abundant in the international literature, studies specifically focused on the Brazilian context remain limited.

Some international studies have directly examined the relationship between accounting standards and forecast accuracy (e.g., Cotter et al., 2012; Glaum et al., 2011). In Brazil, certain investigations have analyzed the impact of IFRS adoption on the accuracy of earnings forecasts (Amato et al., 2016; Silva, 2015; Gatsios, 2013; Pessotti, 2012). These studies have helped to shed light on how international accounting standards have influenced financial reporting practices in the country. Notably, IFRS adoption is considered a potential factor that may affect the accuracy of analysts' projections. However, the research in the Brazilian context is still in its early stages and further studies are required to draw more definitive conclusions.

Within this broader framework, the degree of compliance with specific disclosure requirements may also influence forecast accuracy (Silva, 2015). This is particularly relevant in the case of segment reporting as required by IFRS 8 and its Brazilian equivalent, CPC 22. In the international literature, there is evidence suggesting that the quality and extent of segment disclosure are associated with improved forecast accuracy by analysts (Berger & Hann, 2003). Nevertheless, this specific relationship remains underexplored in studies focused on Brazilian firms.

III. METHODOLOGY

3.1 Sample Selection and Data Collection

To conduct this study, the primary data collected comprised earnings per share (EPS) forecasts. This information was obtained from the Eikon® platform by Thomson Reuters. The platform provides a consensus forecast measure, which corresponds to the average of EPS forecasts for a given company within a specific period. Accordingly, the study collected annual EPS consensus forecasts made by investment analysts, representing market expectations regarding firms' profitability in each respective year.

The selection criteria for the firms included in the study were as follows: (i) the company must have been listed on B3 (Brasil, Bolsa, Balcão) between 2010 and 2017; and (ii) EPS forecasts for the company must be available on the Eikon® platform. The analysis considered forecasts issued between 2010 and 2016, corresponding to earnings for fiscal years 2011 through 2017. This timeframe was selected because it encompasses the initial seven years following the adoption of CPC 22/IFRS 8 in Brazil, thereby allowing for an analysis of disclosure practices during the early implementation period.

Subsequently, financial statements for each firm were collected for the 2010–2016 period. These reports were retrieved from the website of the Brazilian Securities and Exchange Commission (CVM, 2019). Data on actual EPS figures realized by the firms during the same period were also extracted from the Eikon® platform. In addition, information on firm characteristics—used as control variables in the empirical models—was gathered from the B3 website, the Eikon® platform and the Economática® database.

The final sample includes all companies for which complete data were available across the entire analysis period. The resulting dataset comprises 94 companies, distributed across nine distinct economic sectors. Sector classification follows the methodology adopted by B3, which is primarily based on the nature and end use of the products or services offered by each firm.

3.2 Data Analysis and Interpretation

The initial stage of the analysis focused on identifying the segment-related information disclosed by firms. For this purpose, the companies' published annual financial statements were reviewed. The primary objective was to assess the content of the accompanying explanatory notes in order to determine which segment items, as recommended by CPC 22, were disclosed by each company in each fiscal year.

Based on a detailed reading and interpretation of CPC 22, a total of 36 segment reporting items were identified. These items were subsequently grouped into seven categories, as presented in Table 2.

Table 2 – Segment reporting categories

Code	Category
SR_GC	Information on general criteria for defining business segments
SR_QU	Quantitative information by segment (profit, assets, liabilities, income and expenses)
SR_MI	Measurement information
SR_RE	Information on reconciliation
SR_GE	Geographical area information
SR_PS	Product and service information
SR_MC	Information on the main clients

Codes were assigned to facilitate the systematization of items within these categories. Based on this, a data collection instrument was developed to identify the information reported by companies. This instrument consists of a checklist comprising the 36 possible disclosure items, as presented in Table 3.

Table 3 - Instrument for identifying segment disclosure items

Code	Disclosure item
SR_GC1	Criteria for identifying reportable operating segments
SR_GC2	Types of products and services from which each reportable segment derives its revenue
SR_GC3	Segment aggregation criteria
SR_GC4	Description of revenues included in “other segments”
SR_QU1	Profit (or loss) by segment
SR_QU2	Total assets by segment
SR_QU3	Liabilities by segment
SR_QU4	Revenue from external customers (or total revenue) by segment
SR_QU5	Revenue from transactions with other operating segments of the same entity (by segment)
SR_QU6	Financial income and financial expenses (by segment), or net financial result (by segment), including details on their use
SR_QU7	Depreciation and amortization by segment
SR_QU8	Material revenue and expense items disclosed in accordance with item 97 of CPC 26 (by segment)
SR_QU9	The entity's share of profits or losses of affiliates and joint ventures accounted for using the equity method (by segment)
SR_QU10	Income tax and social contribution expense or income (by segment)
SR_QU11	Material non-cash items, except depreciation and amortization (by segment)
SR_QU12	Amount of investment in affiliates and joint ventures accounted for using the equity method (by segment)
SR_QU13	Amount of additions to non-current assets, except financial instruments, deferred income tax and social contribution assets, post-employment benefit assets and rights arising from insurance contracts (by segment)
SR_MI1	The basis of accounting for any transactions between reportable segments
SR_MI2	The nature of any differences between the measures of profit or loss of the reportable segments and the profit or loss of the entity before income tax and social contribution expense (income) and discontinued operations
SR_MI3	Reconciliation of total assets of reportable segments to the entity's assets, separately describing material reconciling items

SR_MI4	The nature of any differences between the measures of the liabilities of the reportable segments and the liabilities of the entity (if not arising from the reconciliations described)
SR_MI5	The nature of any changes from prior periods in the measurement methods used to determine the profit or loss of the reportable segment and the potential effect of these changes on the measurement of the profit or loss of the segment
SR_MI6	The nature and effect of any asymmetric allocations to reportable segments
SR_RE1	Reconciliation of total revenues of reportable segments to the entity's revenues, separately describing material reconciling items
SR_RE2	Reconciliation of total profit amounts of reportable segments to the entity's profit before income tax and social contribution expense and discontinued operations (or reconciliation of total profit amounts of reportable segments to the entity's profit after these items), separately describing material reconciling items
SR_RE3	Reconciliation of total assets of reportable segments to the entity's assets, separately describing material reconciling items
SR_RE4	Reconciliation of total liabilities of reportable segments to the entity's liabilities, if segment liabilities are disclosed, separately describing material reconciling items
SR_RE5	Reconciliation of the total amounts of any other material items of information disclosed by reportable segments to the corresponding amounts of the entity, separately describing material reconciling items
SR_GE1	Revenue from external customers attributed to the entity's home country (domestic market)
SR_GE2	Revenue from external customers attributed to all foreign countries from which the entity derives revenue (external market).
SR_GE3	Non-current assets, excluding financial instruments and deferred income tax and social contribution assets, post-employment benefits and rights arising from insurance contracts, located in the entity's home country.
SR_GE4	Non-current assets, excluding financial instruments, deferred income tax and social contribution assets, post-employment benefits and rights arising from insurance contracts, located in all foreign countries in which the entity maintains assets
SR_GE5	Information by country or subtotals of geographic information on country groups
SR_GE6	Information by geographic region within Brazil
SR_PS	Revenue from external customers for each product and service or for each group of similar products and services
SR_MC	Information on the degree of dependence on its main customers (if revenue from transactions with a single external customer represents 10% or more of the entity's total revenue)

This instrument was applied to the financial statements of each company in the sample. The analysis began by identifying the explanatory notes that specifically addressed information by operating segment. These notes were then examined in detail to determine the presence or absence of each disclosure item listed in the checklist. For each item, a value of 1 was assigned when the information was disclosed and 0 when it was not. This approach reflects the predominantly quantitative nature of the content analysis employed, which enabled the classification and quantification of the information disclosed.

3.2.1 Scoring of Segment Disclosure Levels

In the second phase of the analysis, segment disclosure levels were assessed by assigning scores to companies for each year under examination. The indicator representing segment disclosure levels was constructed using Item Response Theory (IRT), which takes into account the different types of disclosure items reported by companies.

IRT enables the identification of items that are most informative for measuring a given latent construct—in this case, the level of segment disclosure. Among the 36 segment disclosure items recommended by CPC 22, some may be disclosed universally, while others may not be disclosed at all. Such items have limited discriminatory power for distinguishing among companies. IRT addresses this limitation by assigning weights to items based on their ability to differentiate disclosure levels, thereby producing comparative scores that reflect the probability of item disclosure.

According to Pasquali and Primi (2003), IRT is based on two core assumptions: (i) an individual's performance on a given item can be explained by underlying latent traits and (ii) the relationship between item performance and the latent trait can be represented by a monotonically increasing mathematical function known as the Item Characteristic Curve (ICC). IRT also incorporates two key assumptions: unidimensionality, which posits that a single latent trait underlies the observed behavior (Pasquali & Primi, 2003); and local independence, which assumes that responses to different items are statistically independent, conditional on the latent trait level.

To apply IRT, it is necessary to define the metric for the latent trait, typically using a mean (μ) of zero and a standard deviation (σ) of one—i.e., ($\mu = 0, \sigma = 1$)—as noted by Andrade et al. (2000). This standardization allows for the estimation of item parameters on a common scale.

The measurement instrument used in this study consists of a checklist with 36 binary items corresponding to the types of segment information. Each item is coded 1 if disclosed and 0 if not, as presented in Table 3. The IRT model applied is based on dichotomous responses and is designed to measure a latent variable—namely, the level of segment disclosure. The underlying assumption is that companies with a greater propensity for disclosure will have a higher probability of reporting each individual item.

The structural model employed to estimate the latent trait is the two-parameter logistic (2PL) model. As explained by Tezza and Bornia (2009), the 2PL model assumes a monotonic relationship between the latent trait value (θ) and the probability of endorsing an item. This relationship is modeled using a logistic function, parameterized by coefficients representing the item's difficulty and discrimination. The model is specified in Equation 1.

$$P_{ij} = P(U_{ij} = 1 \mid \theta_j) = \frac{1}{1 + e^{-a_i(\theta_j - b_i)}} \qquad (1)$$

Where: i, ranging from 1 to 36, denotes the items designed to assess the latent trait (i.e., the segment reporting items); j, ranging from 1 to n, represents the n companies included in the sample; Uij is a dichotomous variable taking the value 1 when company j discloses item i and 0 otherwise; θj represents the latent trait of company j; P(Uij = 1 | θj is the probability that a company j with latent trait θj discloses item i, referred to as the Item Response Function; e denotes Euler's number (approximately 2.718); ai is the discrimination (or slope) parameter of item i, which is proportional to the steepness of the Item Characteristic Curve (ICC) at point bi; and bi is the difficulty (or threshold) parameter of item i, measured on the same scale as the latent trait and representing the level of the trait θ at which the probability of disclosure is 0.5.

This model was operationalized using R software, employing the "mirt" package (Multidimensional Item Response Theory), version 1.29. During the calibration phase, items that did not effectively discriminate among companies with different levels of segment disclosure were excluded. As a result, the final model includes only those items capable of differentiating firms based on their segment disclosure practices.

From this modeling process, a latent trait score was generated for each company, reflecting its level of segment disclosure. These scores—based on both the type of disclosures and the estimated parameters for each item—constitute the variable "Level of Segment Disclosure" (LSD).

The LSD variable thus quantifies a company's level of segment disclosure. It is expressed on a standardized scale with a mean of 0 and a standard deviation of 1 and should be interpreted accordingly. For example, a company with an LSD score of 1.5 demonstrates a segment disclosure level that is 1.5 standard deviations above the sample average. Conversely, a score of -0.7 indicates a disclosure level 0.7 standard deviations below the mean.

3.2.2 Measuring the Accuracy of Earnings Forecasts Made by Analysts

The third stage of the analysis involved constructing an indicator to measure the accuracy of earnings forecasts made by investment analysts. This indicator was derived by comparing analysts' earnings per share (EPS) forecasts with the actual EPS reported by companies.

EPS forecasts were measured using the consensus forecast—that is, the average of EPS estimates made by sell-side analysts for a given company in a given year (t). Monthly consensus data are available on the Eikon® platform. For each year under review, the consensus value available as of December was selected, as it best represents market expectations regarding the company's performance in that year.

Following the methodology adopted in studies such as Silva (2015), Dalmácio et al. (2013) and Dumer (2012), the forecast error (ERROR) was calculated as an indicator of accuracy. Equation 2 presents the formula used to compute the forecast error.

$$ERROR_{it} = \frac{EPSforecast_{it} - EPS\ actual_{it}}{|EPS\ actual_{it}|} \qquad (2)$$

Where: "$ERROR_{it}$" denotes the forecast error for company i's earnings per share (EPS) for year t; "$EPSforecast_{it}$" is the consensus forecast of EPS made by analysts for company i in year t; and "$EPSactual_{it}$" is the actual EPS reported by company i for year t, disclosed in year t+1. In the denominator of the fraction, "$|EPSactual_{it}|$" represents the absolute value of the actual EPS, used to obtain a standardized relative measure across companies.

Dividing the forecast error by the absolute value of the actual EPS produces a percentage-based error measure that allows for cross-sectional comparability. As the purpose of the analysis is to evaluate the magnitude of deviation between forecasted and actual values—regardless of direction (over or underestimation)—the absolute forecast error (AFE_{it}) is used. It is computed as shown in Equation 3:

$$AFE_{it} = |ERROR_{it}| \qquad (3)$$

Thus, AFE_{it} captures the extent of the forecast error for company i in year t. Higher AFE values indicate larger deviations between forecasted and actual earnings, reflecting lower forecast accuracy. To construct a measure where higher values represent greater accuracy, the AFE value is multiplied by -1, resulting in the variable forecast accuracy ACUR, as defined in Equation 4:

$$ACUR_{it} = (-1) \times AFE_{it} \quad (4)$$

Accordingly, the variable ACUR reflects the precision of analysts' earnings forecasts (Gatsios, 2013; Pessanha, 2012; Cotter et al., 2012; Dumer, 2012; Martinez, 2004). This indicator can take on negative values or zero. The closer the ACUR value is to zero, the smaller the forecast error. Therefore, higher ACUR values indicate greater forecast accuracy.

3.2.3 Investigation of the Relationship Between Segment Disclosure Level and Earnings Forecast Accuracy

It is expected that the disclosure of segment information will improve the accuracy of earnings forecasts by investment analysts operating in the Brazilian market. Given that firms may disclose varying levels of segment information, those with higher disclosure levels are expected to yield forecasts that are more closely aligned with actual earnings. Therefore, the theoretical hypothesis underlying this study is: "The level of disclosure of information by operating segments of Brazilian companies is positively associated with the accuracy of earnings forecasts made by investment analysts."

To test this hypothesis, a linear panel data regression model was employed. The dependent variable is the earnings forecast accuracy (ACUR) and the main independent (explanatory) variable is the level of segment disclosure (LSD). The central statistical outcome of interest is the estimated coefficient β for the explanatory variable LSD, which indicates whether segment disclosure levels are associated with forecast accuracy. The following statistical hypotheses were tested:

- Null hypothesis (H_0): There is no relationship between segment disclosure levels and earnings forecast accuracy ($\beta = 0$).

- Alternative hypothesis (H_1): There is a relationship between segment disclosure levels and earnings forecast accuracy ($\beta \neq 0$).

A significance level of 5% was adopted. In addition to the dependent and explanatory variables, a set of control variables was included in the model to account for other factors that may influence forecast accuracy. These controls aim to isolate the effect of segment disclosure on the dependent variable. The control variables used, along with their definitions and sources, are summarized in Table 4. Their selection was based on prior literature addressing the determinants of earnings forecast accuracy in the context of analyst behavior.

Table 4 – Control variables used in the regression model with panel data

Variable	Operationalization	Data source	Expected sign
Firm size (SIZ)	Natural logarithm of the company's total revenue for the year	Economática®	+
Number of analysts (NUM)	Number of analysts contributing to the earnings forecast consensus	Thomson Eikon®	+
Loss occurrence (LOS)	Dummy variable indicating whether the company reported a loss in the year	Economática®	-
Leverage (LEV)	Ratio of total debt to total assets in the year	Economática®	-
Earnings volatility (VOL)	Percentage change in earnings per share compared to the previous year	Thomson Eikon®	-
Profitability (PRO)	Return on assets (net income divided by total assets) for the year	Economática®	+
Optimism bias (OPT)	Dummy variable indicating whether the forecasted EPS exceeded the realized EPS in the year	Thomson Eikon®	+
Corporate governance (GOV)	Dummy variables indicating whether the firm belongs to one of B3's corporate governance segments	B3	+
Industry (IND)	Dummy variables representing the company's industry classification	Economática®	+/-
Year effects (YEA)	Dummy variables representing each year analyzed	(Not applicable)	+/-

The signs shown in Table 4 represent the expected relationships for the control variables, which may have a positive relationship with accuracy (+ sign) or a negative relationship (- sign). For the variables sector of activity and effects of the years, the relationships are expected to vary (being positive for some cases and negative for others) when considering the different sectors in which the companies operate or the different years of analysis.

The set of control variables is represented by the acronym VC. Thus, the general specification of the regression model adopted is that shown in Equation 5.

$$ACUR_{it} = \alpha + \beta \mathrm{LSD}_{i(t-1)} + \sum_{j=1}^{k} \varpi_j CV_{it}^{j} + e_{it} \quad (5)$$

Where: "$ACUR_{it}$" is the accuracy of earnings forecasts for company i in year t, made by investment analysts (calculated based on the consensus earnings per share); "α" is the model constant; "β" is the slope coefficient of the investigation variable "$LSD_{i(t-1)}$" is the investigation variable, which corresponds to the level of segment disclosure for company i, referring to year t-1; "CV_{it}" represents the k control variables used in the model, referring to company i in year t; "ϖj" are the angular coefficients of the control variables; and "e_{it}" is the error term of the model.

For forecasts made for the company's profit in year t, a positive relationship with the level of information by segment for year t-1 is expected. With access to higher levels of information by segment presented in the previous year, the trend is for earnings forecasts for the respective year to be closer to actual profit figures, i.e., to be more accurate.

According to Fávero and Belfiori (2017), there are three classic approaches to panel data analysis using the ordinary least squares (OLS) method: Pooled Ordinary Least Squares, which considers the beta of an explanatory variable to be the same for all observations over time; Fixed Effects, which, unlike Pooled, considers changes in each observation over time; and Random Effects, which reflects the individual differences in the intercept of each company in the error term.

Stata® software was used to perform the regression analysis. The necessary tests were applied to verify the model assumptions and identify the panel data approach that best fits the research data. Thus, after adjusting the model, it was possible to draw conclusions about the existence of a relationship between the level of information segment disclosure and the accuracy of analysts' earnings forecasts.

IV. RESULTS AND DISCUSSIONS

4.1 Items by Segments Disclosed by Companies

The analysis of the financial statements allowed us to identify the main characteristics of the segment disclosure made by the companies. Specifically regarding the number of segments reported, the results obtained are shown in Table 5. The greater the number of segments, the greater the breakdown of information, as the company's performance is broken down into a greater number of distinct parts. It is worth mentioning that if the company declares that it has a single segment, there is no presentation of quantitative data by segment, since this data would be identical to that contained in the aggregate statements. However, such a company must disclose the items in CPC 22 referring to the entity as a whole, i.e., information on products and services, information on geographical areas and information on major customers.

Table 5 – Percentages referring to the number of segments reported by companies

Number of segments	2010	2011	2012	2013	2014	2015	2016
1 segment	36.17%	34.04%	30.85%	30.85%	29.79%	28.72%	30.85%
2 segments	21.28%	19.15%	23.40%	20.21%	21.28%	22.34%	21.28%
3 segments	12.77%	14.89%	12.77%	17.02%	13.83%	14.89%	15.96%
4 segments	13.83%	18.09%	19.15%	18.09%	19.15%	15.96%	14.89%
5 segments	9.57%	6.38%	7.45%	7.45%	8.51%	10.64%	8.51%
6 segments	5.32%	6.38%	5.32%	5.32%	6.38%	6.38%	6.38%
7 segments	-	-	-	-	-	-	1.06%
8 segments	1.06%	1.06%	1.06%	1.06%	1.06%	1.06%	1.06%

No company disclosed 10 segments, which would be the maximum limit suggested by CPC 22. Those that reported a single segment or two operating segments predominated. In addition, it was found that the percentage of companies that reported 5 to 8 segments ranged from 13.82% to 18.08%. Therefore, what we observe is a low level of information disaggregation for most companies. This result is in line with previous evidence suggesting a low level of information disaggregation in the Brazilian scenario (Souza & Sarlo, 2013; Aillón et al., 2013).

Overall, when analyzing the set of seven categories of reported information, the results reveal that several items were not disclosed by most companies. Since CPC 22 allows freedom in choosing the style of information presentation, different disclosure strategies are observed. The evidence suggests a lack of uniformity in the type and amount of information provided by segment, corroborating what has been pointed out by studies such as those by Schirvic (2014) and Aillón et al. (2013).

4.2 Disclosure Levels by Segment

The variable representing disclosure levels by segment was calculated using Item Response Theory (IRT). The latent trait considered corresponds to the propensity of companies to disclose higher levels of information by segment. Thus, models were estimated that relate the probability $P(\theta)$ of a company disclosing an item to its respective propensity to disclose higher levels of information by segment (θ).

Initially, a model containing all 36 disclosure items on segments analyzed in the previous stage of the research was estimated. The model applied is the one-dimensional logistic model with two parameters (Tezza & Bornia, 2009). In the calibration stage, it was observed that some items did not fit well in this model, since they were not significant in differentiating companies according to the latent trait considered.

In order to analyze the quality of the fit, Bock's chi-square test was performed, whose null hypothesis postulates that there is a good fit for the respective item. Items that presented high values for the $\chi 2$ statistic, with respective p-values lower than 0.01, were excluded from the model. This procedure is adopted because rejection of the null hypothesis of the test indicates that the item does not fit the model well. For the final model, the 16 items with p-values above 0.01 were considered.

Maximum Marginal Likelihood was used to estimate the item parameters and the Bayesian EAP method was applied to estimate the latent traits (Andrade et al., 2000). In the model with two logistic parameters, the estimated parameters are α (discrimination parameter) and β (difficulty parameter). In this case, the discrimination parameter of an item represents the ability of that item to differentiate between companies with different latent traits. On the other hand, a higher value of the difficulty parameter of an item means that a high latent trait is necessary for the company to present the respective item on segments. The results for these parameters are shown in Table 6.

Table 6 – Results of the estimation of the discrimination (α) and difficulty (β) parameters of the logistic model

Item code and corresponding label	α	β
SR_QU3 - Liabilities	1.597	-0.890
SR_QU5 - Revenue from transactions with other segments	2.058	-3.447
SR_QU6 - Financial result	3.584	-1.629
SR_QU7 - Depreciation and amortization	2.566	-1.022
SR_QU8 - Material revenue and expense items	1.756	-2.075
SR_QU9 - The entity's share of profits or losses of affiliates and joint ventures	3.673	-2.327
SR_QU10 - Income tax and social contribution expense or income	3.199	-1.755
SR_QU13- Amount of additions to non-current assets	5.044	-4.771
SR_MI1 - The basis of accounting for transactions between segments	3.079	-3.795
SR_MI2 - The nature of differences between the measures of profit or loss	1.645	-4.075
SR_RE5- Reconciliation of the total amounts of any other material items	1.645	-1.757
SR_GE2 - Revenue from external customers (external market)	0.749	-1.141
SR_GE4 - Non-current assets located in all foreign countries	1.054	-2.928
SR_GE5 - Information by country or subtotals of country groups	0.409	-1.801
SR_PS - Revenue from external customers for each product and service	1.544	-1.198
SR_MC - Information on the degree of dependence on its main customers	0.742	-1.199

Note: A complete description of the items is provided in Table 3.

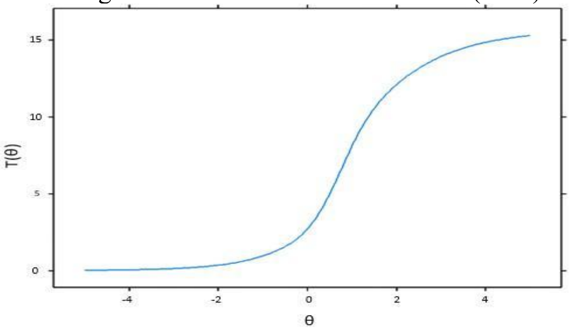
The discrimination parameter allows us to identify which items contribute most to differentiating companies in terms of the level of segment disclosure. Baker (2001) proposes the following classification of the discrimination parameter: a value of 0.0 indicates no discrimination; values from 0.01 to 0.34 indicate very low discrimination; values from 0.35 to 0.64 correspond to low discrimination; values from 0.65 to 1.34 mean moderate discrimination; values from 1.35 to 1.69 represent high discrimination; and values greater than 1.70 indicate very high discrimination.

Using Baker's (2001) classification to analyze the parameters obtained, the results shown in Table 6 show that, of the 16 items, 8 presented very high discrimination (SR_QU5 - Revenues from other segments, SR_QU6 - Financial result, SR_QU7 - Depreciation and amortization, SR_QU8 - Material items of revenue and expense, SR_QU9 - Share in the results of affiliates and joint ventures, SR_QU10 - Income tax and social contribution, SR_QU13 - Additions to non-current assets and SR_MI1 - Basis for transactions between segments) and 4 showed high discrimination (SR_QU3 - Liabilities, SR_MI2 - Differences between measurements of results, SR_RE5 - Reconciliation of other material items and SR_PS - Revenues related to products and services). In addition, three items showed moderate discrimination (SR_GE2 - Revenue from foreign customers, SR_GE4 - Non-current assets located in foreign countries and SR_MC - Information on the degree of customer dependence) and one item showed low discrimination (SR_GE5 - Information by country or groups of countries). Item SR_QU13 contributed most to differentiating companies in terms of disclosure levels by segment, while item SR_GE5 showed the lowest discrimination.

The difficulty parameter ranged from -4.771 to -0.890, which reveals that all types of items are relatively frequent for companies that have a high latent trait. This conclusion is based on the fact that all values for this parameter were negative. The highest value (-0.890) for item SR_QU3 - Liabilities indicates that a higher latent trait is necessary for the company to disclose this item, i.e., that this is a more “difficult” item.

In addition to this analysis of the results by item, a general analysis of the model can be performed. Figure 1 shows the test characteristic curve (TCC) for the model.

Figure 1 – Test Characteristic Curve (TCC)



The TCC represents the probability of obtaining a total score based on the latent trait. As can be seen in the TCC of the model, the results indicate that, on average, a latent trait equal to 0 is necessary for a company to disclose 3 of the disclosure items by segment. Similarly, a company with a latent trait greater than 2 tends to disclose more than 12 items.

Finally, after adjusting the parameters and verifying the model, the latent trait value was assigned to the companies analyzed. The results of the scores referring to the latent trait of each company comprise the variable “Level of Segment Disclosure” (LSD). This variable, which is calculated on a scale of mean 0 and standard deviation 1, represents the levels of disclosure of information by segment presented by the companies, considering the sample and the period analyzed in this study. The higher the value for the LSD variable, the higher the level of disclosure of information by segment carried out by the respective company. Complementing the analysis, the results for the descriptive statistics of the LSD variable are shown in Table 7.

Table 7 – Descriptive statistics of the LSD variable (Level of Segment Disclosure)

Year	Range	Minimum	Maximum	Average	Standard deviation
2010	3.333601	-1.116831	2.216770	0.000120	0.900796
2011	3.314739	-1.220243	2.094496	0.000471	0.898631
2012	3.304743	-1.223465	2.081279	0.000408	0.899117
2013	3.314405	-1.219444	2.094961	0.000163	0.898392
2014	3.268145	-1.245329	2.022815	0.000449	0.901834
2015	3.264655	-1.245948	2.018707	0.000230	0.904697
2016	3.260141	-1.252514	2.007628	0.000568	0.906111

It can be concluded, according to Table 7, that the results for Disclosure Levels by Segment ranged from -1.252514 to 2.216770. Therefore, the company with the lowest LSD had a result approximately 1.25 standard deviations below the disclosure average for the respective year (average referring to the 94 companies in the sample). Similarly, the company with the highest LSD had a result approximately 2.22 standard deviations above the disclosure average for the year.

4.3 Accuracy of Earnings Forecasts Made by Analysts

The descriptive statistics for the accuracy variable, which allows for analysis of the results related to the accuracy of EPS forecasts, are shown in Table 8. Accuracy measures the proximity between the expected value and the actual value, representing the magnitude of forecast errors (Gatsios, 2013; Pessanha, 2012; Cotter et al. 2012; Dumer, 2012; Martinez, 2004). In this case, the possible values for accuracy ranged from -1 to 0; thus, the closer to 0 (zero), the better the accuracy values.

Table 8 – Descriptive statistics for the accuracy variable (ACUR)

Statistic	Value
Mean	-0.26851
Median	-0.12012
Standard deviation	0.32057
Variance	0.10313
Minimum	-0.97821
Maximum	-0.00017

The ACUR variable has a mean of approximately -0.27, a median of -0.12, a standard deviation of 0.32 and a variance of 0.10. The maximum value for ACUR was -0.00017, which reflects an expected value very close to the actual value. In this case, the difference between the expected EPS and the realized EPS corresponded to 0.017% of the realized EPS value, which indicates a good quality of the forecast (since the value is very close to zero). The minimum value of the ACUR variable was -1.0, which reflects a difference between the expected EPS and the realized EPS corresponding to at least 100% of the realized EPS value.

The variations in accuracy that occur over time for each company and those that occur in each of the cross-sections (variation between companies for each year). The variation over time for a given individual (in this case, companies) is called within variation and the variation between companies is called between variation. According to Fávero and Belfiore (2017), the overall variation is the discrepancy that exists in a given data point for an individual at a given moment in time in relation to all other data points for that same variable for the complete base and can be broken down into within variations (over time for each individual) and between variations (between individuals). In this sense, the decomposition of variance for the accuracy of earnings forecasts is shown in Table 9.

Table 9 – Variance decomposition for the accuracy variable (ACUR)

Type of variation	Variance	Percentage
Between	0.0392	38.05%
Within	0.0638	61.98%
Overall	0.1031	100.00%

Table 9 shows that the within-company variance accounts for 61.98% of the total variance. This indicates that the greatest variation in the accuracy of earnings forecasts occurs within each company over time. The variability between companies is relatively smaller, since the between variance represents 38.05% of the total variance. Therefore, these results show that there are variations in accuracy both between companies and over time, which is fundamental for the application of regression models for panel data.

4.4 Results on the Existence of a Relationship between the Level of Segment Disclosure and the Accuracy of Forecasts

Linear regression econometric modeling for panel data was applied to investigate the existence of a relationship between the level of disclosure of information by segment (LSD) of companies and the accuracy of earnings forecasts made by analysts (ACUR). The initial model was estimated using the Ordinary Least Squares (OLS) method. In addition to the dependent variable ACUR and the investigation variable LSD, the model included the following control variables: Company size (SIZ), Number of Analysts (NUM), Losses (LOS), Indebtedness (LEV), Earnings volatility (VOL), Profitability (PRO), Optimistic bias (OPT), Corporate governance (GOV), Industry sector (IND) and Year effects (YEAR).

Initially, the Stepwise procedure was used to identify the control variables that proved significant in explaining the variations in the accuracy of earnings forecasts for the companies in the sample. According to Fávero and Belfiore (2017), the Stepwise procedure automatically excludes explanatory variables whose parameters are not statistically different from 0 (zero). By applying this procedure, it is possible to define the control variables that effectively contribute to explaining the variations in accuracy in the analyzed context.

The VIF (variance inflation factor) statistic was applied to verify the existence of possible evidence of multicollinearity among the independent variables in the model. The VIF indicator ranged from 1.01 to 1.84 for all variables, confirming the absence of multicollinearity. The VIF must be less than 5 for the regression to be acceptable and this requirement was met for all variables. Therefore, there were no problems with regard to the multicollinearity of the variables.

The White test was used to verify the homoscedasticity of the residuals. In the final model, the test returned a value of 155.4556 with a p-value of less than 1% (0.0000). Thus, heteroscedasticity of the residuals in the model was detected and corrected using White's covariance matrix with robust standard errors (Fávero & Belfiore, 2017).

Tests were also applied to identify the best approach for panel data (Chow test, Breusch-Pagan test and Hausman test). The results of these tests are presented in Table 10.

Table 10 – Test results to identify the best fit for panel data

Statistic	Chow	Breusch-Pagan	Hausman	Best Fit
Result	2.0122	25.4067	9.3112	Random Effects
P-value	0.0000	0.0000	0.3167	

As shown in Table 10, with the application of the tests, the Random Effects approach proved to be the most appropriate for the data analyzed. Thus, the final research model was estimated using the Random Effects approach with robust standard errors. The results of this model are presented in Table 11.

Table 11 – Results of the regression with Random Effects and robust standard errors for the dependent variable accuracy (ACUR)

Variable	Coefficient	Robust standard error	T-statistic	Probability
LSD – Level of Segment Disclosure	-0.019125	0.016305	-1.17	0.241
SIZ – Firm size	0.025980	0.010114	2.57	0.010**
NUM – Number of analysts	0.011942	0.003786	3.15	0.002***
LOS – Loss occurrence	-0.258374	0.050809	-5.09	0.000***
LEV – Leverage	-0.168004	0.065123	-2.58	0.010**
PRO – Profitability	0.096858	0.048844	1.98	0.047**
OPT – Optimism bias	0.084837	0.025081	-3.38	0.001***
IND – Industry	-0.128143	0.036426	-3.52	0.000***
YEAR_2012 – Year effects of 2012	0.058189	0.024473	2.38	0.017**
_CONS – Model constant	-0.591058	0.142332	-4.15	0.000***
Number of observations = 658		R^2 *within* = 0.1650		
Wald χ^2 (9) = 257.61		R^2 *between* = 0.5588		
Prob > χ^2 = 0.0000		R^2 *overall* = 0.3115		

Note: The asterisks indicate the significance level of the coefficients: ***(1%), **(5%) and *(10%).

The bottom part of Table 11 shows the parameters related to the model adjustment. The Wald chi-square value (Wald χ2) was statistically significant at 1% (p-value of 0.0000), indicating that the Random Effects estimate is consistent. This result ensures that there is at least one independent variable coefficient that is significant (Fávero & Belfiore, 2017).

It is also important to note that the overall explanatory power, represented by the overall R2, is 31.15%. Thus, the variables included in the model explain about 31% of the variations in the accuracy of earnings forecasts. The model explains 55.88% of the variation in accuracy between companies (R2 between) and 16.50% of the variation in accuracy over the years for each company (R2 within).

Analyzing the estimation results and the outputs of the model estimated by Random Effects, it can be observed that eight control variables were statistically significant as explanatory factors for the accuracy of earnings forecasts for companies in the years under analysis. This is verified from the Wald Z statistic values, which presented p-values lower than 0.05 (i.e., they were significant at 5%).

However, no statistically significant relationship was identified between the LSD variable and the ACUR variable. The main result obtained with the model is the Wald Z statistic value equal to -1.17 for the LSD variable. The respective p-value of 0.241 is greater than 0.05 and, consequently, does not allow the null hypothesis to be rejected. Thus, at a significance level of 5%, the theoretical hypothesis that level of segment disclosure would be positively related to the accuracy of analysts' earnings forecasts is not confirmed.

As no statistically significant value was identified for the LSD variable coefficient, the results show that there is no relationship between this variable and ACUR (accuracy). It can therefore be inferred that the fact that companies provide higher levels of segment information did not favor the accuracy of earnings forecasts for these companies.

V. CONCLUSION

This study aimed to investigate the existence of a relationship between the level of segment disclosure of Brazilian companies and the accuracy of earnings forecasts made by investment analysts. Based on the application of the regression model for panel data, it was found that the segment disclosure indicator did not contribute to explaining the variations in the accuracy of forecasts.

The levels of segment disclosure were measured based on the set of information by segment disclosed in each company's explanatory notes and the probabilities of presentation of each type of item by segment. The results showed that these levels varied among companies, as managers have discretion to define disclosure strategies.

The main conclusion was that the level of disclosure of segment information by Brazilian companies is not related to the accuracy of earnings forecasts made by investment analysts. Thus, earnings forecasts were no more accurate for companies with higher levels of disclosure, which would be expected given the basic principle of segment reporting advocated in Brazil. Although this disclosure was proposed with the aim of detailing the nature and financial effects of the business activities in which the company is involved and the economic environments in which it operates, the results provide evidence that higher levels of segment information do not significantly improve analysts' perception of companies' profit-generating capacity.

Therefore, the evidence from this research reinforces the argument that the characteristics of segment reporting currently carried out by companies limit the usefulness of the information reported and that higher levels of disclosure do not improve the accuracy of earnings forecasts. As noted, the low levels of disaggregation in the segment reporting provided by the companies in the sample may also undermine the usefulness of segment information for earnings forecasts.

Finally, it should be noted that the presence of certain types of information in financial statements does not guarantee that such information is useful. For segment disclosure to be relevant, it is necessary that such segments be defined and reported in a way that allows analysts to use their expertise to make their forecasts, adequately assessing the financial position and future prospects of companies. The evidence gathered in this study supports this argument and suggests the need to improve segment disclosure in the Brazilian context. These findings contribute to the literature by showing that, in an emerging market context, mandatory segment reporting may not fulfill its expected role in improving forecast accuracy.

It is important to mention that the results obtained should be considered in light of the limitations of the methodology adopted in this study. The indicator used to measure the level of segment disclosure was developed based on CPC 22 and other types of items that companies may have classified as segment information were not incorporated into the analysis. In addition, the levels of segment disclosure were measured based on Item Response Theory, but other approaches could be used. Regarding the application of the regression model for panel data, other variables that may have some influence on the accuracy of earnings forecasts were not addressed. Therefore, the results and interpretations are subject to the definition of the proxies used, the sample and the period analyzed.

For future research, we suggest interviewing investment analysts about the use of segment reports in their earnings forecasting process. Another recommendation is to analyze individually the relevance of each type of item by segment disclosed by companies, identifying whether some items may be more useful than others for improving earnings forecasts.

Finally, it should be noted that no previous evidence has been identified regarding the existence of a relationship between segment disclosure and the accuracy of earnings forecasts for companies in Brazil. There are opportunities for the development of new empirical research that can aid in understanding the impacts caused by such disclosure on the Brazilian capital market and the agents involved in it.

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