

# Do intangible assets matter to financial analysts in the Brazilian stock market?

518

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## Abstract

**Purpose** – This paper aims to investigate how and to what extent intangible assets influence the evaluations of financial analysts covering companies listed on the Brazilian Stock Exchange (*Brazil, Bolsa, Balcão – B3*) from 2010 to 2016.

**Design/methodology/approach** – The analysis was divided into two stages. In the first stage, we examined intangible asset taxonomies (i.e., structural, relational, and human capital) through content analysis by counting repeated key terms related to each category of intangible assets cited in the financial analysts' reports. In the second stage, we analyzed the influence of intangible asset proxy variables on coverage, forecasting errors, and accuracy of earnings per share forecasts by financial analysts.

**Findings** – In the first stage, the results suggested that analysts cited more terms related to the structural capital category, particularly the terms “strategy” and “mission.” In the second stage, the results pointed to the absence of statistically significant relationships between the studied variables. Therefore, it is possible to infer that although financial analysts covering firms in the Brazilian Stock Exchange cite terms related to intangible assets in their reports – which, in turn, points to the relevance of these assets during the company valuation process – the difficulty of conducting evaluations grounded on reliable bases, the scarcity of quality information about their development, and incentive problems may challenge or even prevent quantitative assessments targeted at capital market participants.

**Originality/value** – By adopting an innovative methodological approach in the Brazilian context, this study highlights the fact that intangible assets influence financial analysts to a certain extent and they, in turn, manage to incorporate them into their analyses, although the statistical relationships have not been explicitly demonstrated.

**Keywords** – Intangible Assets, Financial Analysts, Brazilian Stock Market.



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## 1 Introduction

Intangible assets are the main drivers of corporate value. Through brands, patents, know-how, software, processes, contracts, and goodwill, among others, companies around the world have achieved a competitive advantage, as tangible assets have rapidly become commodities (Lev & Gu, 2016).

Despite the relevance of intangibles, there are accounting and financial limitations to evaluating them (Cavalcanti, Amaral, Correia, & Louzada, 2017). On the one hand, accounting standards and legal procedures do not allow intangibles to be fully reported in financial statements; they are recorded as expenses. On the other hand, financial valuation methodologies need to be adjusted, as it is difficult to format expectations regarding the inputs needed to prepare the cash flows generated by such assets.

This paper puts forward the idea that financial analysts – the information intermediaries between companies and investors – are agents capable of overcoming such limitations. We agree with Bessieux-Ollivier, Schatt, Walliser, and Zéghal (2014) that analysts are sophisticated users of accounting, financial, market, and economic information, who have the potential to supplement intangible asset information by incorporating expectations of future corporate performance in their analyses and disclosing them afterwards to capital market participants through their reports.

One of the main abilities of analysts is to identify undervalued securities in the capital market that may represent investment opportunities (Barth, Kasznik, & McNichols, 2001). These opportunities are more frequent in intangible-intensive companies (Amir, Lev, & Sougiannis, 2003) because information about their main value-driving assets is not readily available to the market. Thus, we assume that financial analysts have the required know-how to evaluate these assets and to give buy, sell, or hold recommendations for these companies.

International empirical evidence shows that financial analysts can complement information on intangible assets through their earnings forecasts. This is made possible by their market expertise, as well as the acquisition and retention of accounting, financial, and private information obtained through meetings with managers (Bradshaw, 2011).

When covering intangible-intensive companies, financial analysts' forecast errors increase (Gu & Wang, 2005). This is due to the conflicts of interest inherent to the work they perform, which may hinder or even prevent the evaluation of intangibles (He & Tian, 2013). Moreover, it can also be due to the uncertainty of cash flows from intangible assets, which can make their values speculative (Penman, 2009).

In addition to earnings forecasts, analysts can supplement information on intangible assets through the market-perception analyses disclosed in their reports. In developed countries, empirical evidence derived from using the content analysis methodology in financial analyst reports indicate that these professionals cite key terms related to intangible assets, revealing their perceptions of the relevance of intangibles to corporate performance (García-Meca, Parra, Larrán, & Martínez, 2005; García-Meca & Martínez, 2007; Abdolmohammadi, Simnett, Thibodeau, & Wright, 2006; Maaloul, Ben Amar, & Zeghal, 2016).

In emerging markets, the performance of financial analysts may be even more relevant to complement information on intangible assets, given that information asymmetries are potentially greater (Hsu & Chang, 2011; Elbannan, 2013). Therefore, seeking to emphasize the relevance of intangibles to financial analysts in the Brazilian context, our objective was to examine how and to what extent these assets influenced the recommendations of analysts have covered companies listed on the Brazilian Stock Exchange (B3 – *Brasil, Bolsa, Balcão*) between 2010 and 2016.

Our analyses were performed in two stages. In the first, we examined how intangible

assets influence analysts' evaluations. To this end, we presented a research proposal that was verified by analyzing the frequency of keywords related to intangible assets in analysts' reports. In the second stage, we examined the extent of this influence. For this, we tested three research hypotheses that related a proxy for intangible assets to financial analyst variables (coverage, errors, and accuracy in profit forecasting), using panel data regression.

Our results suggest that although financial analysts working in the Brazilian stock market make references to intangible assets in their reports – which points to the relevance of these assets – the difficulty of evaluating them, the scarcity of quality information about the development of such assets, and incentive problems discourage or even prevent their evaluations in quantitative terms for the participants of the capital market. To date, this is the first paper to address the influence of intangible assets on the evaluations of financial analysts in Brazil, using the proposed methodology. It seeks, therefore, to contribute to filling this gap in the literature on the subject.

This paper is structured in five sections, in addition to this introduction. Section 2 discusses intangible assets and their taxonomies, before moving on to discuss their influence on financial analysts' evaluations. Section 3 presents the research methodology adopted herein. Section 4 describes and discusses the results. In the fifth and final section, the conclusions are presented.

## 2 Literature Review

### 2.1 Intangible assets

Intangibles are the set of assets that are not physical in nature, which are under the control of the company and from which future economic benefits are expected, thus being cash flow inputs (Zéghal & Maaloul, 2011). This concept is linked to the methodology of discounted cash flow (DCF), where the value of an asset is obtained by adding up the present value of its net future benefits. Within the definitions of intangible assets, they are generally grouped by taxonomies

divided into three major capital categories: 1) human; 2) structural; and 3) relational (Petty & Guthrie, 2000).

The human capital category assumes that the generation of corporate value resides in the individuals that make up the organization. To this end, the International Integrated Reporting Council – IIRC (2013) proposes that the competencies, motivations for innovation, capabilities, experiences, and loyalty of such individuals are aligned with the organization's structure, objectives, risk management, and ethical values.

More broadly, relational capital is characterized by the building and strengthening of the social relationships promoted by companies, not only with their internal public but mainly with their external public (Reed, Lubatkin, & Srinivasan, 2006). In this regard, the IIRC (2013) considers that relations between companies and the social space aim to connect key stakeholder groups by sharing common norms and behaviors based on willingness and commitment to create and protect values, which are sometimes reflected in the brand, in the philosophy, in the networks of relationships, in the mission, and the reputation of companies.

Finally, structural capital represents the combination of explicit and implicit knowledge, both formal and informal, which coexist within organizational structures, in order to allow the perpetuated development of its activities, products, services, processes, information systems, and objectives aimed at creating value in a sustainable way (Martín-de-Castro *et al.*, 2011).

By listing the key terms concerning the taxonomies of intangible assets, it was possible to identify an important corpus of empirical evidence, especially in developed countries, which analyzed the incidence of such terms in the analysts' reports. For instance, García-Meca *et al.* (2005) and García-Meca and Martínez (2007) observed that strategic (structural) intangible assets are most emphasized in analysts' reports covering Spanish companies. Similarly, Maalou

*et al.* (2016) documented that while the analysts' emphasis on the categories of intangibles was different among the companies in the S&P 500 index, the structural category was the most cited.

The evidence suggests that financial analysts disclose information concerning

companies listed on the stock exchanges that they regard as the most relevant; added to that, intangible assets are expected to be addressed as part of this information (Abhayawansa, 2011), particularly structural ones. Therefore, we propose that:

$P_1$  Structural intangible assets are the most cited by financial analysts in their evaluation reports.

This proposition is also based on the literature review by Reina and Ensslin (2011), who demonstrate that the strategy of companies was emphasized by empirical studies on intangible assets in Brazil. During the development of this research, no empirical studies were found focused on analyzing the content of financial analyst reports in the Brazilian context, in order to identify the influence of intangibles on the asset valuations described in them.

## 2.2 Financial Analysts

Financial analysts are specialized, sophisticated users of financial statements and information related to macroeconomics and capital markets (Bradshaw, 2011; Ramnath, Rock, & Shane, 2008). They are commonly regarded as agents that reduce information asymmetry between companies and investors (Jensen & Meckling, 1976). This is because their work consists of disseminating investment analysis through their evaluation reports, which enable a reduction in informational gaps (Kothari, So, & Verdi, 2016).

There are basically two categories of financial analysts: sell-side and buy-side. Buy-side analysts work for institutional investors such as mutual, pension, and hedge funds, and their recommendations are kept private and exclusive for their employers and customers (Groysberg, Healy, Serafeim, & Shanthikumar, 2013). In turn, sell-side analysts are hired by brokerage firms or investment banks to gather information about company performance so that it can be projected in future

terms. To achieve this, they should produce at least one report per year (Fogarty & Rogers, 2005). This paper analyzed information prepared by sell-side analysts, given the availability of data.

Analysts' reports usually provide buy, sell, or hold recommendations. As a result, the activities of analysts are permeated by conflicts of interest, which are not related to deviations from moral or ethical conduct, punishable by their supervisory bodies. As Mehran and Stulz (2007) pointed out, these conflicts are observed in situations in which one party involved in a transaction can potentially make direct gains by taking actions that negatively affect the other party. As examples, these authors mention two cases: 1) by making buying recommendations, analysts may facilitate the development of a profitable relationship between investment banks and recommended companies, which could become a frequent practice; and 2) as a broker's revenue source derives from brokerage fees, upgrades and buy recommendations may result in more trading volume than downgrade reviews and sell recommendations.

Another aspect inherent to analysts' recommendations is the possibility of bias. Acknowledgment that financial analysts have an optimistic bias in their investment recommendations, due to the conflicts of interest discussed above, is often found in international empirical evidence (Bradshaw, 2011). Similarly, Martinez (2007a) and Lima and Almeida (2015) found evidence of optimistic bias in analysts' recommendations in Brazil.

This problem can be worsened in the assessment of intangible assets, since most of them are not fully reported in the financial statements, making it difficult for analysts to identify them immediately (Lev & Gu, 2016). Consequently, they tend to make more forecast errors when covering intangible-intensive companies (Gu & Wang, 2005).

Also, financial analysts are active agents who seek positive results for their clients, which, in turn, can have adverse effects on companies. According to He and Tian (2013), the pressure imposed by analysts on company management for short-term results makes it myopic in terms of long-term investments in general, represented by intangible assets. The bottom line is that in order to invest in these assets, it is necessary to have a certain level of tolerance to short-term failure, given their inherent risks, as well as some sort of

long-term reward as a means to reward the effort in the case of success.

In this sense, Barth, Kasznik, and McNichols (2001) demonstrate that evaluating intangible assets demands greater effort from financial analysts due to the need to seek additional information about them. However, in intangible-intensive companies, this becomes attractive as analysts identify investment opportunities in them. This happens because if we assume that the intrinsic values of intangible-intensive companies do not necessarily reflect their capacity to generate future value, then their shares would be poorly priced in the capital market. Amir, Lev, and Sougiannis (2003) assume that analysts understand and somehow capture the potential value of intangible assets, even with the problems involved in their recognition in financial statements. Based on these arguments, the first hypothesis of this research is postulated:

$H_1$  As investments in intangible assets by intangible-intensive companies increase, financial analysts' coverage increases.

Barron, Byard, Kile, and Riedl (2002) and Gu and Wang (2005) stated that evaluating intangible assets on a reliable basis is a very labor-intensive task and that analysts who attempt to

do so typically commit forecast errors – despite the potential of these professionals to supplement information on these assets. Hence, the second hypothesis of this research is:

$H_2$  As investments in intangible assets by intangible-intensive companies increase, financial analysts' forecast errors increase.

In addition to the expectation that analysts' forecast errors are more frequent in intangible-intensive firms, we also expect the accuracy of their forecasts to be lower. This is because the

values of intangible assets are imprecise (Penman, 2009). Therefore, the third hypothesis tested in this research is:

$H_3$  As investments in intangible assets by intangible-intensive companies increase, financial analysts' accuracy decreases.

In Brazil, the relationship between intangible assets and asset valuations performed by financial analysts has only been previously analyzed by Antunes and Leite (2008). These authors concluded that while financial analysts consider intangibles in their investment recommendations, the poor quality of corporate information regarding the value creation of such assets makes their valuation challenging. Therefore, this paper innovates within the scope of asset valuation, as it analyzes how and to what extent intangibles influence financial analysts in the Brazilian context, besides contributing to a better understanding of this relationship.

Internationally, the seminal article by Barth, Kasznik, and McNichols (2001) found that, on the one hand, financial analysts follow and recommend intangible-intensive companies due to their underpricing in the capital market, which would configure a window of opportunities for investments; on the other hand, analyzing and identifying them requires significant effort from these professionals. Similarly, Barron *et al.* (2002) documented that there is less consensus in analysts' forecasts and that individual error is more frequent in intangible-intensive companies, so that the way found to compensate for this risk is to rely more extensively on private information. When investigating whether analysts' recommendations compensate for the lack of information on intangible assets in financial statements, Amir, Lev, and Sougiannis (2003) found that the valuations of these professionals partially complement the value of such assets, and this contribution is accentuated in intangible-intensive companies. In line with this evidence, the results of Gu and Wang (2005) revealed a positive relationship between analysts' forecasting errors and the intensity of intangible corporate assets, which indicates a higher degree of complexity in predicting the future performance of these companies. Given this, He and Tian (2013) concluded that analysts pressure corporate management for short-term results, making management short-sighted and hampering

the development of innovation and long-term investments, such as in intangible assets. Similar results were found in developing countries, such as Egypt (Elbannan, 2013).

Studies on financial analysts developed in the Brazilian context have focused on different aspects compared to this study. In general, the Brazilian empirical evidence has revealed that: (i) the financial analysts' forecasts are positively biased (Franco, 2002; Lima & Almeida, 2015; Martinez, 2007a); (ii) the "learning by doing" effect has controversial results (Martinez, 2007b; Lima, 2017); (iii) buy recommendations predominate (Martinez, 2010); (iv) the analysts' actions increase transparency in the capital markets (Martinez, 2011); and (v) good corporate governance practices improve the financial analysts' earnings forecasts (Almeida & Dalmácio, 2015; Dalmácio, Lopes, Rezende, & Sarlo, 2013).

### 3 Methodological Procedures

#### 3.1 Sample, data, and variables

The empirical study presented in this paper was conducted in two stages. In the first, we investigated how intangible assets influence analysts in their evaluations of companies. In particular, we analyzed the content of their reports using computer-aided text analysis. The use of this innovative strategy in the Brazilian context sought to support the research proposal by identifying the key terms related to the categories of intangibles, namely human capital, structural capital, and relational capital, which were the most cited in the analysts' reports. One hit was counted for each term identified, and this procedure was performed throughout the reports collected. A detailed description of these terms can be found in Appendix A.

The criterion for selecting reports was the company's permanence in the "Novo Mercado" index of the B3, between 2014 and 2016. This Brazilian index indicates better corporate governance practices and less significant information asymmetries (Almeida & Dalmácio,

2015). From this selection of companies, analyst reports with at least one Thomson One® StarMine were chosen, as they are regarded as being from the best analysts in this database in terms of forecast accuracy. Finally, the sample comprised 44 companies from nine sectors, and the reports of sell-side financial analysts linked to 19 brokerage companies were analyzed.

In the second stage, we tested the three hypotheses postulated for this research and verified, through panel data regression, the extent to which intangible assets influence financial analysts' evaluations. The sample initially comprised 961 active and inactive companies listed on the B3. After excluding companies in the financial sector and also those without an industry classification, according to Bloomberg®, 693 companies remained. We then excluded from the sample the companies with negative equity in any year of the analysis. After applying this filter, 597 remained. Next, we excluded the

companies lacking the necessary information to calculate the dependent, independent, and control variables, with 370 firms remaining. Finally, we excluded the companies that did not present data for number of analysts during the analyzed period. Therefore, the sample consisted of 178 non-financial companies listed in the B3 between 2010 and 2016, forming an unbalanced panel. The sample period is justified because two relevant facts occurred in 2010: 1) the mandatory harmonization of Brazilian accounting norms with the international standards; 2) the certification requirement to act as a financial analyst in Brazil.

The proxies for intangibles (independent variables) and the financial analysts' evaluations (dependent variables) are described in Table 1. The data needed to calculate the analyzed variables were collected in the Bloomberg® database, except for the number of patents, which was collected from Orbis®.

Table 1  
Operationalization of Variables

Variable	Description	Acronym	Formula	Authors
Dependent Variable: Proxy for Financial Analysts				
	Coverage	COV	$COV = \ln(1 + \text{number of analyst}_{it})$	Barth, Kasznik, and McNichols (2001)
	Forecast error	FE	$FE_{it} = \frac{X_{it} - F_{it}}{P_{i,t-1}}$ FE = forecast error of earnings per share (EPS); X = EPS; F = consensus of analysts' EPS forecasts for the following 12 months, estimated in December; P = closing price of the company's stock one day before the end of the month in which the consensus of the analysts' forecasts was released.	Ramnath, Rock, and Shane (2005)
	Accuracy	AC	AC (accuracy) = a dispersion estimate. It is calculated based on the standard deviation of the forecast estimate for firm i in time t, scaled by the share price of firm i in time t.	Almeida and Dalmácio (2015)
Independent Variables: Proxy for Intangible Assets				
	Intangible assets	IA	$IA = \frac{\text{Intangible Assets}_{it}}{\text{Total Asset}_{it}}$	Barth, Kasznik, and McNichols (2001)
	Number of patents	PAT	$PAT = \ln(\text{number of patents}_{it})$	Teh, Kayo, and Kimura (2008).

Variable	Description	Acronym	Formula	Authors
Independent Variables: Performance Proxy (Control)				
Effort		EFF	EFF = negative average number of companies followed by financial analysts in relation to a specific company. The average number of companies was multiplied by -1 so that the effort is an increasing measure. As Barth, Kasznik, and McNichols (2001, p. 11) have clarified, "if a company is followed by three analysts who cover five, six, or seven companies, respectively, the effort equals -6."	Barth, Kasznik, and McNichols (2001, p. 11)
Independent Variables: Performance Proxy (Control)				
Turnover		TUR	$TUR = 1/D_t \sum_{t=1}^T \frac{Volume_{it}}{Shares\ Outstanding_{it}}$	Lesmond (2005)
Profitability		PROF	$PROF = \frac{EBITDA_{it}}{Total\ Asset_{it}}$	Macedo, Machado, Murcia, and Machado (2012)
Size		SIZE	$SIZE = \ln(\text{market value}_{it})$	Gu and Wang (2005)
Market-to-book		MTB	$MTB = \frac{P_{y,i,t} \times N_{y,i,t}}{Equity_{it}}$ Where: P = type y share price of company i, in t; N = number of type y shares of company i, in circulation in t.	Mussa, Famá, and Santos (2012).
Beta		BETA	$\beta_i = \frac{\sigma_{iM}}{\sigma_M^2}$ $\sigma_{iM}\sigma_{iM} = \text{covariance between the return of asset i and the market index and } \sigma_M^2 \sigma_M^2 \text{ variance of the market index returns.}$ Beta is calculated based on the return of the assets in a period of 60 months (minimum of 24 observations), using the Bovespa index (Ibovespa) as the market return and the CDI (interbank deposit certificate) as a risk-free asset proxy.	Kayo, The, and Basso (2006)

Note: The subscripts *i* and *t* refer to the firm and the year, respectively.

### 3.2 Econometric models

In relation to hypothesis 1, the positive relationship between intangible assets and analysts' coverage was tested using equation [1]. To identify the intangible-intensive companies,

we employed the third quartile of the frequency distribution of the intangible variable scaled by total assets, evidenced in the balance sheet. "Intangibles" denote the proxy variables for intangibles – IA and PAT. Six control variables related to firm performance were included.

$$COV_{it} = \beta_0 + \beta_1 Intangibles_{it} + \beta_2 EFF_{it} + \beta_3 PROF_{it} + \beta_4 SIZE_{it} + \beta_5 MTB_{it} + \beta_6 BETA_{it} + \beta_7 TUR_{it} + d\_intensive_{it} + \varepsilon_{it} \quad [1]$$

where:  $\beta_0$  = intercept; *Intangibles* = proxy for intangible assets measured alternately by IA and

PAT; *EFF* = effort; *PRO* = profitability; *SIZ* = size; *MTB* = market-to-book; *BETA* = market



risk;  $TUR$  = liquidity;  $d\_intensive$  = dummy variable of intangible-intensive firms;  $\varepsilon$  = error term; the subscripts  $i$  and  $t$  refer to the firm and the year, respectively.

$$FE_{it} = \beta_0 + \beta_1 Intangibles_{it} + \beta_2 EFF_{it} + \beta_3 PROF_{it} + \beta_4 SIZE_{it} + \beta_5 MTB_{it} + \beta_6 BETA_{it} + \beta_7 TUR_{it} + d\_intensive_{it} + \varepsilon_{it} \quad [2]$$

where: FE = analysts' forecast errors. Finally, hypothesis 3, which presupposes an inverse

In regard to hypothesis 2, the positive association between investments in intangibles and analysts' forecast errors was tested using equation [2].

association between accuracy and investments in intangibles, was tested using equation [3].

$$AC_{it} = \beta_0 + \beta_1 Intangibles_{it} + \beta_2 EFF_{it} + \beta_3 PROF_{it} + \beta_4 SIZE_{it} + \beta_5 MTB_{it} + \beta_6 BETA_{it} + \beta_7 TUR_{it} + d\_intensive_{it} + \varepsilon_{it} \quad [3]$$

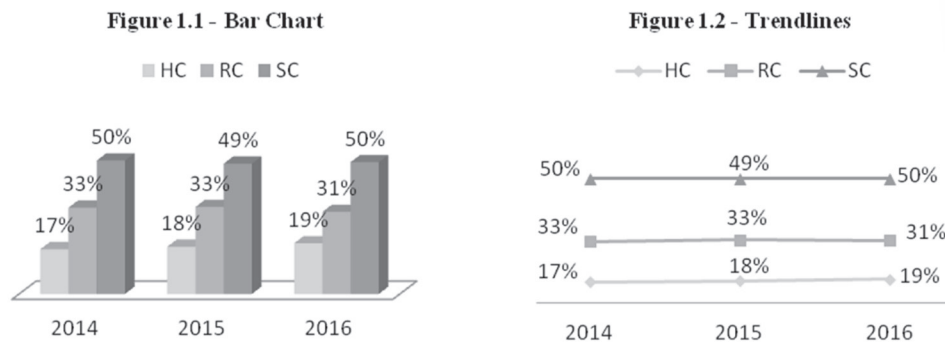
where: AC = accuracy. All models were estimated for each intangible proxy variable.

## 4 Results and Discussion

### 4.1 First step: content analysis

The results obtained through the relative frequency analysis of the number of hits found in each of the three categories of intangible assets adopted are shown in Figure 1. It shows that among the keywords belonging to each category

of intangibles, structural capital (SC) presented a higher relative frequency, corresponding to about 50% of the total hits. Following that, human capital accounted for approximately 32% and, finally, relational capital corresponded to the remaining difference of 18%. Also, it is possible to observe constant behavior in the distribution of the relative frequency of the three categories of intangible assets over the three years analyzed – Figure 1.2 shows the constant trend line.



**Figure 1.** Relative frequency of content analysis by category and year

Our results corroborate our research proposal and are in line with international empirical evidence. For example, García-Meca

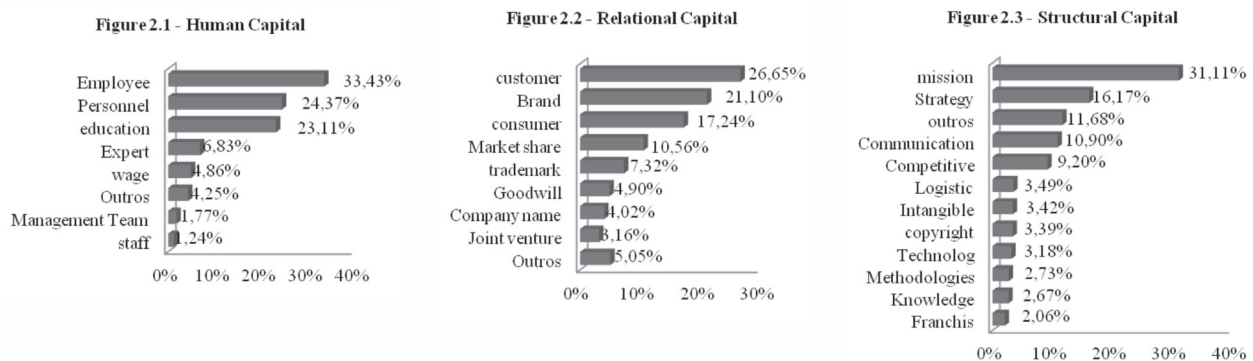
*et al.* (2005) and García-Meca and Martínez (2007) showed that structural assets were the most cited category of intangible assets in Spain since

financial analysts were more concerned about disclosing information regarding the consistency of the company's strategy implementation. A higher average incidence of structural capital was also found in the financial reports of analysts who follow companies listed on the United States stock exchange, according to the results found by Maaloul *et al.* (2016).

The national empirical evidence does not directly correspond to the results of this research. Antunes and Leite (2008) found that financial analysts are more concerned about human capital. However, as the methodology employed is different in both studies, this may have led to divergence between our results and those found by Antunes and Leite (2008). Therefore, we consider that this research adds to the study of Antunes and Leite (2008) to contribute to a better understanding of the value of intangibles, insofar as it contextualizes their disclosure by financial analysts in the national context and compares them with the international ones.

Figure 2 illustrates the relative frequency of the most significant keywords in each category of intangibles. These analyses are reported in general terms, i.e., the number of hits for the entire analysis period were added up.

In the human capital category, illustrated in Figure 2.1, the most significant keywords are "employee" and "personnel," followed by "education," "expert," "wage," and "management team." In Figure 2.2, it is possible to verify that "customer" and "consumer" are among the most significant keywords in the relational intangibles category, followed by "brand," "market share," "trademark," "goodwill," "company name," and "joint venture." In Figure 2.3, "mission" and "strategy" are the most significant keywords in the structural capital category, followed by "communication," "competitive," "logistic," "intangible," "copyrights," "technology," "knowledge," and "franchise." It should be noted that the term "others" comprises all other keywords that had a minimal percentage incidence of hits and were, therefore, grouped together.



**Figure 2.** Relative frequency of content analysis, by the most significant keyword

By analyzing the keywords individually and reusing the terms that characterize the intangible assets categories, such as "relational capital," "human capital," and "structural capital," no hits of these words were found.

In this sense, Abhayawansa (2011) argues that one of the main limitations of content analysis in financial analyst reports may concern

the writing style. While it may be assumed that analysts are unaware of the terms "relational capital," "human capital," and "structural capital," it is also plausible to assume that such practitioners use different terminologies to refer to intangibles. Tsui, Wang, Cai, Cheung, and Lee (2014), for instance, consider that keywords related to the categories of intangibles are forcibly academic,

so it is paramount to be familiar with the jargon of capital markets in order to better identify the keywords used by analysts.

The results found at this stage of the research suggest that analysts emphasized terms related to mission and corporate strategy. In management textbooks, a company's mission and strategy are sometimes linked to prospective information, i.e., to how the company communicates to its users the management strategy adopted to achieve its objectives. In this way, it is possible for analysts to use this information in order to evaluate the ability of a company to generate future economic benefits on the current date. These results are in line with the analyses carried out by Reina and Ensslin (2011), which point out that national and international research on intangibles is more focused on the strategic perspective.

Therefore, we conclude that financial analysts take intangible assets into account in their investment recommendation reports. More specifically, structural intangibles, that is, those generated internally, are emphasized. As pointed out by Lev and Gu (2016), to collect this data analysts access additional information, such as meetings with CEOs and CFOs of the companies under evaluation.

#### 4.2 Second step: panel data regressions

Table 2 presents the descriptive statistics for the variables concerning the analysts: the

number of financial analysts who recommended buying, selling, or holding stocks traded on the B3, as well as the total number of analysts covering companies and the consensus recommendation. On average, we can observe a higher number of analysts recommending buying and holding stocks. The maximum values of these variables and the average recommendation rating reinforce this interpretation.

This descriptive analysis is in line with the arguments of Ramnath, Rock, and Shane (2008), where the authors argue that analysts are reluctant to recommend selling stocks as a result of retaliatory acts they may suffer from either their employer, their clients, or the company being evaluated. As Bradshaw (2011) explains, it is understandable that analysts more often recommend buying or holding stocks in view of the conflicts of interest inherent in their business environment. Also, if the analyst makes a forecasting error, selling is the only recommendation that cannot be reversed, as the loss will have already been consummated.

In that sense, finding optimistic bias in Brazilian financial analysts' forecasts would not be an unexpected result as this bias has already been observed in other studies, such as those conducted by Lima and Almeida (2015) and Martinez (2007a).

Table 2

#### Descriptive statistics of variables related to financial analysts

	Consensus	Hold	Sell	Buy	Total Analysts
Obs.	886	1043	1043	1043	1043
Mean	3,75	4,05	1,01	4,59	9,66
SD	0,78	3,53	1,80	3,96	6,49
min	1	0	0	0	0
max	5	18	14	18	27
p25	3,3	1	0	1	4
p50	3,83	3	0	4	10
p75	4,3	6	1	7	15

*Note.* The acronyms stand for: Obs. = number of observations; mean = mean; SD = standard deviation; min = minimum value; max = maximum value; p25 = first quartile; p50 = median; p75 = third quartile. Data collected from 178 non-financial firms listed in the B3 in the period 2010-2016.

After the initial analysis of the database, the descriptive statistics of the variables to be estimated in the regression model were performed, as shown in Table 3. The descriptive statistics of the variables referring to the financial analysts are in line with the data in Table 2. In particular, the forecast error variable presented a negative mean value, which reinforces the argument that analysts may present optimistic bias in their evaluations. It should be noted that the forecast shown in Table 3 corresponds to December, that is, the most recent forecast issued by the analyst prior to the end of the period.

On average, the intangible assets shown in the financial statements corresponded to 19% of total assets, with maximum values of 91%, and the average number of patents was 33, with a maximum value of 424. As for corporate performance, profitability represented, on average, 11% of total assets. The average turnover was low, and its maximum value was less than 1,

which indicates moderate liquidity of the sample. The effort values were negative according to their definition.

Also, Table 3 shows values with high standard deviations, such as the value of the market-to-book variable. This result was expected because certain companies in the sample have a much higher market value than their book value, and this is reflected in the dispersion of this variable. As a strong indication of value creation from intangible assets is attributed to market-to-book (Lev, 2001), and financial analysts in emerging markets are significantly impacted by it (Moshirian, Ng, & Wu, 2009), this variable was not standardized.

Based on the descriptive statistics, it is concluded that the financial analysts who recommend assets listed in the B3 deal with quite heterogeneous companies, which may make their evaluations challenging, especially when they cover various companies simultaneously.

Table 3  
Descriptive statistics of dependent and independent variables

	Obs.	Mean	Standard Deviation	Minimum	Maximum	p25	p50	p75
COV	1043	2.08	0.86	0	3.33	1.61	2.40	2.77
FE	644	-0.23	2.71	-60.10	13	-0.07	-0.02	0.0004
AC	793	0.040	0.22	0	3.97	0.004	0.01	0.02
IA	1137	0.19	0.21	0	0.91	0.02	0.12	0.29
PAT	333	2.11	1.69	0	6.05	0.69	1.94	3.46
EFF	1077	-30.63	22.80	-191	-4	-32.5	-25.5	-19.4
PROF	1148	0.11	0.09	-0.31	0.68	0.06	0.10	0.15
SIZE	962	14.96	1.62	10.22	19.75	13.91	15.05	15.99
MTB	957	2.43	3.47	0.02	51.78	0.8	1.43	2.82
BETA	945	0.74	0.45	-0.47	2.89	0.44	0.69	1
TUR	944	0.003	0.004	0	0.49	0.001	0.002	0.004

Note. The abbreviations stand for Coverage (COV), Forecast error (FE), Accuracy (AC), Intangible assets (IA), Number of patents (PAT), Effort (EFF), Profitability (PRO), Size (SIZ), Market-to-book (MTB), Beta (BETA), Turnover (TUR), Obs. = number of observations. Data collected from 178 non-financial firms listed in the B3 in the period 2010-2016.

Table 4 shows the estimated results for each econometric specification proposed in this paper: 1) the ones reported in Panel A refer to hypothesis 1; 2) those reported in Panel B refer

to hypothesis 2; 3) those reported in Panel C refer to hypothesis 3. In each of the panels, the codes (A1, A2, B1, B2, C1, and C2) are related to the estimates that used as the proxy for intangibles

the values of such assets as reported in the Balance Sheet (represented by 1 after the respective letter of the reference panel); and the natural logarithm of the number of patents (represented by 2). In the three models, panel data regressions were estimated by fixed effects, with robust standard errors for autocorrelation and heteroscedasticity through Driscoll-Kraay correction, as shown in Tables 4 and 5.

From analyzing the proxies of intangible assets, we realize that the results did not present statistically significant relationships with any of the financial analysts' variables (Table 4). When we reclaim the arguments of Lev (2001), this result seems counterintuitive. Nonetheless, to understand the Brazilian context, we can resort to empirical evidence that is in line with this research. For instance, the papers of Carvalho, Kayo, and Martin (2010), Miranda, Vasconcelos, Silva, Santos, and Maia (2013), Nascimento, Oliveira, Marques, and Cunha (2012), and Santos, Basso, Kimura, and Kayo (2014) did not find significant relationships between intangible proxies and corporate performance. Thus, the results of Table 4 are partially aligned with the national empirical evidence, given the absence of a statistically significant association between proxies for intangible assets and, in our case, financial analysts' forecasts.

Regarding the control variables, it can be seen in Table 4 that "effort," a variable suggested by Barth, Kasznik, and McNichols (2001), presented, in some cases, the behavior expected by the literature. On the one hand, the relationship between "effort" and forecast errors was positive and statistically significant, i.e., the greater the effort required to evaluate a company, the higher the forecast error. This suggests that the incidence of analysts' forecast errors is greater when they cover a larger number of firms simultaneously. However, the coefficient of this variable was too low and cannot be considered economically relevant. On the other hand, "effort" proved to be positively associated with "coverage," reaching 1% significance. In the Brazilian context, this

can be understood insofar as informational asymmetries can sometimes be considered as obstacles to collecting quality corporate information, which makes the analysts' task more challenging, requiring a greater effort on their part to differentiate their recommendations from those made by other analysts. Also, it is possible that brokerage firms employing analysts encourage/reward coverage of a larger number of firms, which in turn would increase their efforts to evaluate them correctly.

In Table 4, the relationships between the financial analysts' variables and the controls "profitability" and "size" showed opposite signs to those expected, except for the association between "coverage" and "size" (Panel A), which was positive and statistically significant. In Panel B, it can be seen that the "profitability" and "size" impacts on analysts' forecasting errors are positive and significant. In Panel C, it is possible to observe a significant negative association between "size" and "accuracy" in the forecasts, although the coefficients are economically irrelevant. This can be justified insofar as these variables refer to companies with more complex organizational structures, either because they have a higher market value and, consequently, a greater plurality of funding channels, or because the profitability of their business originates from diverse economic segments.

In the estimates of Table 4, the market-to-book variable was statistically significant in all models, but in none of them was the sign as expected. Also, the coefficients related to this variable were very low concerning the other variables and, therefore, failed to demonstrate economic relevance for the analysis.

The relationship between "liquidity" and "accuracy" was significant and as expected (Panel C); that is, the greater the volume of trading, the greater the accuracy of analysts' forecasts. Liquidity thwarted expectations but was not statistically significant in both panels.

Finally, the variables coverage, forecast errors, and accuracy of financial analysts' forecasts

are assumed to be affected by the systemic risks of the companies; that is, by the variations in the returns of the companies' shares due to variations in market returns. This is justified insofar as it would not be possible for the analyst to diversify this type of risk. To control this effect in the estimated models, the proxy employed for systemic risk was the beta variable. In general, the relationships between these variables did not demonstrate statistical significance, except for the estimates of Panel B.1. As expected, the analysts' earnings forecast errors were more frequent in companies with higher systemic risk.

In summary, from the results presented in Table 4, it was verified that the estimates for intangible assets reported in the Balance Sheet were the most statistically consistent. This is possibly due to the greater number of observations in the sample for this variable compared to the number of patents. In this sense, Barth *et al.* (2001) comment that analysts rely on accounting and market information to make their corporate

performance forecasts, which is not the case of patents since they would not have easy access to this type of information. Despite the criticisms related to the value of the intangible assets shown in the financial statements, which is often much lower than the intangibles that the company actually owns (Lev & Gu, 2016), this value represents a starting point for the analysis – especially when one considers that the information on other intangible proxies presented insufficient data in Brazil. Also, Penman (2009) argues that the value of intangibles reported in the Balance Sheet reflects what accounting can measure reliably regarding their value and, because it is objective, it may demonstrate some potential for its use in decision making. It should be noted that in this study additional proxy variables for intangible assets were collected, such as research and development expenses and marketing expenses. However, these variables lacked enough data to estimate the regressions and were therefore excluded from the analyses.

Table 4  
Estimates of panel data regression models without control of intangible-intensive companies

	Pred	Panel A		Pred	Panel B		Pred	Panel C	
		(A.1)	(A.2)		(B.1)	(B.2)		(C.1)	(C.2)
Intangible assets	+	0,0649 (0,140)		+	-0,0569 (0,351)		-	-0,0401 (0,0742)	
Number of patents	+		0,000227 (0,0162)	+		-0,00214 (0,00737)	-		0,000284 (0,00190)
Effort	-	0,00726*** (0,00125)	0,00446*** (0,000915)	+	0,00801*** (0,00169)	0,00217 (0,00209)	-	-0,000140 (0,000448)	0,000355 (0,000266)
Profitability	+	0,0814 (0,370)	-0,454 (0,251)	-	2,003*** (0,537)	1,632** (0,598)	+	0,117 (0,139)	0,00941 (0,0205)
Size	+	0,227*** (0,0285)	0,290*** (0,0551)	-	0,156*** (0,0274)	0,184*** (0,0359)	+	-0,0599* (0,0270)	-0,0302** (0,00898)
Market-to-Book	+	-0,00437 (0,00397)	-0,0363** (0,0116)	+	-0,0185 (0,00962)	-0,0233** (0,00661)	-	0,000974 (0,00136)	0,00349*** (0,000183)
Beta	-	0,112 (0,0693)	0,0296 (0,0768)	+	0,201* (0,0851)	0,0790 (0,0541)	-	0,0138 (0,0128)	-0,00235 (0,00594)
Liquidity	+	-2,524 (3,048)	-1,786 (6,124)	-	-34,97 (26,08)	4,222 (3,447)	+	2,110* (1,056)	3,076*** (0,354)
Constant		-1,146** (0,400)	-1,986** (0,771)		-2,538*** (0,492)	-3,143*** (0,597)		0,923* (0,396)	0,482** (0,151)

	Panel A		Pred	Panel B		Pred	Panel C	
	(A.1)	(A.2)		(B.1)	(B.2)		(C.1)	(C.2)
Number of observations	804	312		617	249		726	293
VIF	1,25	1,32		1,23	1,32		1,24	1,31
Chow test (prob > F)	0,0000	0,0000		0,0001	0,0076		0,0000	0,0000
Hausman test	44,29***	28,95***		3,64	32,4***		13,16*	20,39**
Breusch-Pagan test	-	-		0.62	-		-	-

*Note.* The asterisks \*, \*\*, and \*\*\* refer to the statistical significance levels of 10%, 5%, and 1%, respectively. The values in parentheses are the standard errors. VIF means “variance inflation factor.” The acronym “Pred” refers to prediction and shows the expected sign. The estimates for Panels A, B, and C were obtained through the fixed effects model and are robust to heteroscedasticity and autocorrelation, including panel B.1, for standardization purposes. The estimator of the panel data regression models is “ordinary least squares” (OLS), robust to autocorrelation and heteroscedasticity through Driscoll-Kraay correction. The Chow test verifies the null hypothesis of the pooled model against the alternative hypothesis of fixed effects. The Breusch-Pagan test verifies the null hypothesis of the pooled model against the alternative hypothesis of random effects. The Hausman test verifies the null hypothesis of random effects against the alternative hypothesis of fixed effects.

The analyses presented in Table 4 constitute the complete sample; that is, the intangible-intensive companies were not controlled separately from the others. However, as the research hypotheses refer to intangible-intensive companies, we analyzed them separately. In this sense, Table 5 presents the same estimates of the regression models of Table 4, with the difference that a dummy variable was created to distinguish intangible-intensive companies. This dummy was based on the frequency distribution of the variable “intangible assets” scaled by total assets, where intangible-intensive companies receive a value of 1 if they have intangible asset values scaled by total assets equal to or greater than the third quartile of the sample, and 0 otherwise. In making this separation, we identified that approximately 31.54% of the sample corresponds to intangible-intensive companies.

The results presented in Table 5 are consistent with those presented in Table 4, in all their relevant aspects. Briefly, this means that the intangible assets did not have a statistically significant influence on the coverage, errors, and accuracy of the analysts’ forecasts, nor on the whole sample in general or the intangible-intensive companies in particular. Consequently, all the hypotheses of this research were rejected. Also, the dummy variable of intangible-intensive

companies showed statistical significance, in line with the expected sign in the results of Panels A and B. Therefore, the companies with the largest volume of intangible assets in their asset structure attract broader coverage of analysts, which increases the errors in their earnings forecasts. This is justified insofar as these companies have more complex valuations, which exposes the analysts to a greater risk of errors in their forecasts.

However, this does not suggest that intangibles do not matter for financial analysts in the context of the Brazilian stock market. As found in the first analysis stage, these professionals cite terms related to intangibles in their reports. Possibly, analysts believe that intangible assets are relevant but do not attribute value to them in monetary terms or any other metric scale, for the evaluation of these is more complex, compared to other types of assets. Besides, little additional information about the value of these assets is disclosed by the companies, making their evaluation even more difficult. When analysts try to evaluate them, they are likely to incur errors, which could, in turn, damage their careers. Finally, conflicts of interest may discourage them from undertaking efforts to evaluate intangibles, especially in the Brazilian stock market.

As for the variables of corporate performance, it was verified that the most

consistent were effort, profitability, size, and market-to-book. In this sense, financial analysts seem to be influenced by performance indicators

at firm and market levels, as demonstrated by Pace, Basso, and Silva (2003) in the Brazilian context.

Table 5  
Estimates of panel regression models for intangible-intensive companies

	Pred	Panel A		Pred	Panel B		Pred	Panel C	
		(A.1)	(A.2)		(B.1)	(B.2)		(C.1)	(C.2)
Intangible Assets	+	-0,0330 (0,155)		+	-0,0933 (0,386)		-	-0,0391 (0,0855)	
Number of Patents	+		0,00471 (0,0187)	+		0,000251 (0,00747)	-		0,000131 (0,00205)
Effort	-	0,00721*** (0,00124)	0,00437*** (0,000984)	+	0,00796*** (0,00163)	0,00208 (0,00214)	-	-0,000139 (0,000471)	0,000368 (0,000277)
Profitability	+	0,109 (0,375)	-0,404 (0,246)	-	2,010** (0,550)	1,654** (0,611)	+	0,117 (0,145)	0,00796 (0,0200)
Size	+	0,225*** (0,0280)	0,280*** (0,0547)	-	0,155*** (0,0287)	0,180*** (0,0364)	+	-0,0599* (0,0274)	-0,0298** (0,00881)
Market-to-Book	+	-0,00399 (0,00412)	-0,0348** (0,0115)	+	-0,0184 (0,00967)	-0,0226** (0,00638)	-	0,000970 (0,00142)	0,00344*** (0,000175)
Beta	-	0,113 (0,0690)	0,0385 (0,0733)	+	0,201* (0,0864)	0,0848 (0,0521)	-	0,0138 (0,0129)	-0,00264 (0,00601)
Liquidity	+	-2,551 (3,053)	-2,309 (6,143)	-	-34,97 (26,10)	4,022 (3,391)	+	2,110* (1,055)	3,088*** (0,353)
Dummy intensive	+	0,0644 (0,0526)	0,227** (0,0755)	+	0,0207 (0,0768)	0,122** (0,0386)	-	-0,000642 (0,0153)	-0,00690 (0,00468)
Constant		-1,114** (0,393)	-1,904* (0,778)		-2,529*** (0,510)	-3,115*** (0,601)		0,922* (0,403)	0,479** (0,150)
Number of observations		804	312		617	249		726	293
VIF		1,94	1,33		1,93	1,33		1,93	1,33
Chow test (prob > F)		0,0000	0,0000		0,0001	0,0075		0,0000	0,0239
Hausman test		49,31***	28,71***		3,57	32,38***		13,22*	19,33**
Breusch-Pagan test		-	-		0,66	-		-	-

*Note.* The asterisks \*, \*\*, and \*\*\* refer to the statistical significance levels of 10%, 5%, and 1%, respectively. The values in parentheses are the standard errors. VIF means “variance inflation factor.” The acronym “Pred” refers to prediction and shows the expected sign. The estimates for Panels A, B, and C were obtained through the fixed effects model and are robust to heteroscedasticity and autocorrelation, including panel B.1, for standardization purposes. The estimator of the panel data regression models is “ordinary least squares” (OLS), robust to autocorrelation and heteroscedasticity through Driscoll-Kraay correction. The Chow test verifies the null hypothesis of the pooled model against the alternative hypothesis of fixed effects. The Breusch-Pagan test verifies the null hypothesis of the pooled model against the alternative hypothesis of random effects. The Hausman test verifies the null hypothesis of random effects against the alternative hypothesis of fixed effects.

## 5 Conclusion

This paper analyzed how and to what extent intangible assets influence financial analysts’ evaluations in the Brazilian stock market. To this end, the analyses were divided into two

stages: the first stage (1) investigated the content of the reports and the second (2) examined two proxy variables for intangible assets and three variables concerning the evaluation by financial analysts.



The first stage was developed through content analysis. Our goal was to identify which categories of intangible assets financial analysts cite most in their reports. When defining a set of keywords for each of the three categories of intangibles, we identified that the “structural capital” category was the most cited by analysts. Analysts particularly emphasize the terms “mission” and “strategy” in their reports.

We analyzed the second stage through panel data regression analysis. Intangible assets were represented by the number of patents and the value of intangible assets reported in the Balance Sheet, while the variables related to financial analysts were measured by coverage, errors, and accuracy of their earnings per share forecasts. Our results suggest that the relationships between intangible assets and coverage, forecast errors, and accuracy in analysts’ forecasts are not statistically significant or economically relevant.

Therefore, our results suggest that although financial analysts covering firms listed in the Brazilian stock market make references to intangible assets in their reports – which points to the relevance of these assets – the difficulty of evaluating them, the scarcity of quality information about the development of such assets, and incentive problems discourage or even prevent their evaluations in quantitative terms for capital market participants. Therefore, intangible assets matter to financial analysts to some extent and they somehow manage to incorporate them into their analyses.

Despite the innovative methodological approach of this study, we highlight as a limitation the fact that the selected keywords are overly academic and may not correspond to the jargon used by financial analysts to refer to intangible assets in their reports. In addition, the proxy variables for intangible assets adopted are limited to patents, and their disclosed value in the financial statements.

For future research, we suggest investigating the financial analysts’ environment in Brazil, as there may be local idiosyncrasies in that context

that make their task even more challenging, especially when it comes to the evaluation of intangible assets. Also, we suggest conducting research that performs an intersection between the disclosure of intangible assets in financial analysts’ reports and quantitative analyses using regression models and we recommend searching for more refined proxies for intangible assets.

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