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Learning, Portfolio Complexity and Informational Asymmetry in Forecasts of Sell-Side Analysts

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ABSTRACT

The aim of this study was to analyze the association of learning and complexity in the target price forecasts and sell-side analysts' recommendations on the BM&FBovespa. The sample comprised forecasts of 195 stocks, 75 brokers and 569 analysts between 2005 and 2013, analyzed by linear models with panel data. Our results suggest that the experience with the stock, with the sector and complexity of the portfolio confirmed the learn by doing, but the overall experience showed contradictions due to information asymmetry. Despite anchoring in their peers, analysts achieved significant returns, but showed forecasts with low accuracy. Therfore, we concluded that more experienced analysts may intentionally contradict themselves in an attempt to bias the market. Finally, we suggest the development of less biased analyst rankings in order to increase the competitiveness and quality in the results of the analyzes.

Keywords: Financial analysts; Target price forecast; Stock recommendations; Learning; Portfolio complexity.

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1. INTRODUCTION

The financial market analysts regularly conduct target price and profit forecasts in order to support their recommendations to buy and sale assets on the stock market. For such purpose, they use tools and ability to price these assets at a given time horizon. Issued reports aim to provide good analyzes to their customers, contributing to operations that enable maximizing investors returns (CHUNG; JO, 1996).

In the exercise of their activities, there are elements that improve or deteriorate the performance of these forecasts. However, few studies have observed these mechanisms in the Brazilian market, which shows the need to verify how these professionals practice, how they observe their mistakes and those by their peers. Based on these elements, we can verify how their forecasts and recommendations can be improved (MARTINEZ, 2007; 2008; 2009).

This study aimed to analyze the association of learning and complexity of the portfolio in sell-side analysts' target price forecasts and recommendations considering the information asymmetry on the BM&FBovespa. The learning analysis in the forecast is a reflection of the evolution of performance with the experience in the industry, the complexity of the hedging portfolio and the informational effect of the revisions in analyzes.

Research by Mikhail, Walther and Willis (1997) investigated the effects of learning by repetition, based on learn by doing, with the argument that the abilities of each individual are not homogeneous. The metrics used as a proxy for experience, based on the number of forecasts performed repeatedly in a given period, including categorization by asset and sector.

The results by Mikhail, Walther and Willis (1997), as those by Jacob, Lys and Neale (1999) and Clement (1999) demonstrate ample evidence that the experience with the firm in the North American market contributes to improvements in accuracy. These surveys focus on observing whether these experience metrics promote improvements in their results, observing recommendations' accuracy and returns. In the analysis of experience, we can observe whether analysts are performing new analysis or just replicating previous reports.

The complexity of the hedging portfolio is another factor that affects the analyst's cognitive ability. Clement (1999) provides evidence that the increased complexity, which is the number of companies and sectors that the analyst covers in their portfolio, reduces accuracy. This effect is especially important for brokers, for it contributes to observe ways in which analysts can organize themselves into teams which enable better results.

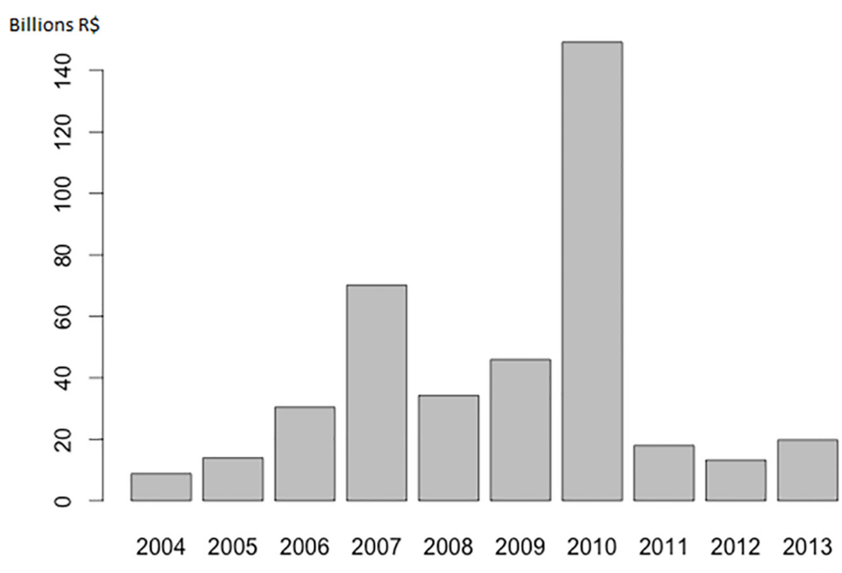
Informativity also influences the activity, because the role of analysts is to convey information through their analysis, as well as the ability to use this disclosed information. This measure, from the learning perspective, seeks to observe the ability to absorb and verify their own mistakes and those by their peers in face of previous forecasts, or if analysts are simply copying modifications previously made (BRAV; LEHAVY, 2003; ASQUITH; MIKHAIL; AU, 2005).

Despite the empirical evidence, there are elements in the Brazilian market showing evidence that some of these mechanisms of improvements do not work the same way as in the countries investigated. Studies by Martinez (2007, 2008 and 2009) and Saito, Villalobos and Benetti (2008) show evidence that in Brazil, analysts present lower performance than in other markets such as the North American. Furthermore, economic characteristics can also influence this process, as the market instability, smaller amount of traded assets, the differentiated amount of the investor population and, especially by the absence of effective mechanisms that promote competition in the industry.

In Brazil there are few rankings and awards that encourage improvements in the activity. We enumerate the Institutional Investor ranking that works by the voting of managers, the award of the Association of Investment Analysts and Professionals of the Capital Market (APIMEC) that works by vote among peers and the ranking of the State Agency Broadcast which analyzes only registered analysts for the return of their recommendations. Some of these mechanisms are questioned due to biases that their methodologies present (EMERY; LI, 2009).

Another reason for this research is due to the growth in the volume of public offerings in recent years, see Figure 1. The growth in the number of traded assets and increased informational efficiency reinforce the idea that analysts' experience and their portfolios complexity are following the evolution and the increase in transactions (MOBAREK; FIORANTE, 2014).

Evidence in Brazil found by Martinez (2009), using earnings forecasts show that there are improvements with the experience, but no effects were observed on the complexity of hedging



Source: BM&FBovespa.

Figure 1. Volume of IPOs in recent years in Brazil.

portfolio. Given the lack of research in the Brazilian market, and specificities in relation to other markets already researched, this gap motivated the need to understand how analysts improve their forecasts and recommendations abilities, especially by analyzing the target price, a variable which is little explored.

The advantage of the target price use are evidence of aspects less conflicting than earnings forecasts. This consideration is based on the following results: (i) target price forecasts seem to be less biased by influences such as conflicts of interest of individuals, and (ii) the effect of informational target price revisions have greater information content than revisions of earnings forecasts. Such evidence indicate attractiveness for the analysis of this variable (ASQUITH, MIKHAIL, AU 2005; KERL, 2011).

This research is distinguished for its approach of the period between 2005 and 2013 in the Brazilian market, as well as the learning effects with regard to target price forecasts and recommendations (buy/sell/hold) by sell-side analysts. We believe that the evidence of improvements in forecasts and recommendations in emerging markets such as Brazil allows us to assume that the relationship between learning, portfolio complexity and accuracy may demonstrate new behaviors, including observation of how the improvement of this process occurs over time.

This work was structured as follows: topic 2 presents a survey of previous empirical evidence; topic 3 describes the performance metrics used; topic 4 lists the hypotheses based on previous studies; topic 5 explains the data sample used; topic 6 details the method used based on the previous items; topic 7 analyzes the results; and topic 8 the final considerations.

2. PREVIOUS STUDIES

Research addressing analysts' forecasts are began over half a century ago, starting with discussions on the role of analysts (e.g. Godfrey, 1953). Ramnath, Rock and Shane (2008) and Bradshaw, Brown and Huang (2013) summarize that most studies investigate forecasts based on corporate earnings estimates, based on exploring the determinants of good forecasts and the existence of biases of agents in the development of this activity.

According to Bradshaw (2002), target price forecasts are used by analysts as a way to support the recommendations to their investor clients. When the recommendation suggests buying, the prediction is that the company's value is undervalued; when holding is suggested the asset presents an approximately fair value, and when selling is suggested, the expectation is that the company's value is overvalued.

Brav and Lehavy (2003) and Asquith, Mikhail and Au (2005) performed na informational analyzed and observed significant market impact by revisions of the target price forecasts, as well as the revisions of recommendations and earnings forecasts. The key point by Brav and Lehavy

(2003) is that analysts converge the degree of recommendation to convey confidence in their price forecast. Based on this argument, Brav and Lehavy (2003) confirmed the argument by Bradshaw (2002) that forecasts support recommendations.

However, there is evidence that this relationship between forecast and recommendation presents moments of informational asymmetry, because analysts are better informed than investors. This asymmetry can stimulate changes in interest and modifications in the status of recommendations (BRADSHAW, 2002). In some cases, these incentives provide an imbalance in analyst reports, which in somecases therefore, will prefer not to disclose their analyzes.

his effect of suppressing certain analysis is termed as self-selction bias, which means that analysts prefer not to disclose price forecasts when these do not support their recommendations or when they are uncertain about their estimates (BRADSHAW, 2002). When this occurs more often, recommendations in some cases may present imbalances in the buy, hold and sell ratio. For this reason, Francis and Soffer (1997) argue that the trend in the proportion of reports to buy rather than to hold and sell is intentional.

Considering the imbalance in recommendations, Asquith, Mikhail and Au (2005) observed the differentiation between revisions for less (downgrades) and revisions for more (upgrades). An important sign is that investors react more significantly when reports show reviews for less (downgrades). The excess of buying recommendations and information asymmetry can explain the reason for optimism normally observed by research.

The results presented by the imbalance of forecasts and recommendations also allow criticism regarding metrics. In the Italian market, Bonini *et al* (2010), in turn, criticize the traditional metric of accuracy, especially by signs of no reversion to the mean and the autocorrelation. These elements make it difficult to analyze the determinants, which affects previous evidence. For this, it is necessary to use models for analysis to correct these aspects. Although investors do not consider the accuracy of target prices as a differential, as they focus on recommendations, the metric is defended by Bradshaw, Brown and Huang (2013) as an important measure of the analyst's performance, as it is a way to validate the recommendation.

Kerl (2011), in the German market, also focused on analyzing the accuracy of target prices, but from another viewpoint. The main results show persistence in accuracy, as well as in buying recommendations, which corroborates the effects previously discussed. In spite of this, Bradshaw, Brown and Huang (2013) analyze the determinants and the behavior of errors over time and show that analysts have limited capacity to persistently perform forecasts with accuracy.

In Brazil, few studies were dedicated to the research of analysts covering companies on the BM&FBovespa, we can cite studies by Martinez (2007), investigating the optimism of analysts' forecasts in the Brazilian market; Martinez (2008), who analyzes the impact of revisions of projections; and Martinez (2009), who investigates the determinants of accuracy. The main findings by Martinez (2007) were: the poor accuracy performance and forecasting errors, which are corelated to prior period errors, which is also evidence found in Martinez (2008).

Martinez (2009) shows that analysts of Brazilian companies showed a persistent optimism on average. Despite the optimism, the result by Martinez (2008) complements the evidence that there are moments of pessimism in the market, demonstrating different impacts for negative and positive revisions. But the most evident in this latest survey is that the Brazilian market is more sensitive to bad news than developed markets such as the North American.

Recently, the research by Dalmacio *et al* (2013) analyzed the impact of governance practices in the accuracy of analysts. The research presents strong relationships in improving the accuracy in the level of the firm's corporate governance. On the other hand, the research by Matinez and Dumer (2014), which analyzes the effect of the performance on the adoption of International Financial Reporting Standards - IFRS in Brazil, no significant association of improvements with this change were observed.

The studies by Saito, Villalobos by Benetti (2008), on the other hand, investigate the determinants of the quality of forecasts of market analysts. The research points out the reasons why analysts in Brazil have lower performance, among the limitations: (1) difficulties related to the economic instability of the country; (2) the limitations of analysts' abilities in the Brazilian market, especially in relation to more sophisticated statistical models; and (3) the stability of the economy and the results of companies in other markets are more easily foreseen. In general, it is confirmed in research by Martinez (2007, 2008 and 2009) and Saito, Villalobos and Benetti (2008) that the Brazilian market for financial analysts need improvements in the quality and performance of the services offered.

3. PERFORMANCE METRICS

Despite recent criticism on the ways of measuring the accuracy and bias by Bonini *et al* (2010), in this study we opted for the classic metrics used in previous studies, as the evidence found were not clearly different from those found by the metrics already used. We summarized by using bias, the accuracy, returns and informativity of forecasts and recommendations.

3.1. Bias

This metric attempts to capture the forecasting errors. Equation 1 refers to *Percentage Forecast Error* from the percentage difference between *Forecast Price,* which is the expected price months before and the Last Price, closing price months after the forecast. This metric reflects the bias of estimates, considering each asset at time . If the average of forecast errors is negative and significant, then the forecasts were higher than the results, demonstrating optimistic bias. If positive and significant, then there is a pessimistic bias (BRADSHAW; BROWN; HUANG, 2013).

$$PFE_{ijt} = \frac{LP_{ijt} - FP_{ijt}}{LP_{ijt}} \qquad (1)$$

3.2. Accuracy

Equation 2 tries to capture the absolute error, *Percentage Absolute Forecast Error,* obtained by the absolute percentage relationship between the *Forecast Price,* which is the expected price months before and the *Last Price,* closing price months after this forecast. This metric reflects the accuracy of forecasts, considering each analyst , asset at time . The closer the averages of are to zero, the greater the accuracy (BRADSHAW; BROWN; HUANG, 2013).

$$PAFE_{ijt} = \left|\frac{LP_{ijt} - FP_{ijt}}{LP_{ijt}}\right| \qquad (2)$$

3.3. Returns for the recommendation

The gain from the buy/hold/sell rating recommendation, termed as is the analyst's recommendation for the period. The recommendation is rated on a continuous scale from 1 to 5, in which 1-sale, 2-weak sale, 3-hold, 4-weak buy, 5-buy. The annual cumulative return *Cumulative Returns of Recommendation* is calculated by the recommendation of the return for months derived from the difference between the last price negotiated months before and the price negotiated subsequently (BRADSHAW; BROWN; HUANG, 2013).

The return calculation on the recommendation is performed by Equation 3, wherein the accumulated return is calculated according to the recommendation , considering each analyst , asset at time . This return is nothing more than the percentage difference of positions to buy and sell assets.

$$CRR_{ijt} = \begin{cases} LP_{ij(t-n)}/LP_{ijt} - 1 & caso\ 1 \leq REC_{ijt} < 3 \\ 0 & caso\ REC_{ijt} = 3; \\ LP_{ijt}/LP_{ij(t-n)} - 1 & caso\ 3 < REC_{ijt} \leq 5; \end{cases} \qquad (3)$$

We also used *Cumulative Market-Adjusted Return* calculated by adjusting the cumulative return to the market in the equation 4. The adjusted return is derived from the mean difference between the return of recommendation and the market return *Cumulative Market Return* for each time period . The market return is calculated by the return from the variation of the index score that represents the market (BRADSHAW; BROWN; HUANG, 2013).

$$CMAR_{ijt} = CRR_{ijt} - CMR_t \qquad (4)$$

3.4. Informativity

The informativity metric measures the association between revisions of forecasts of analysts and the abnormal returns on assets . According to Givoly and Lakonishok (1979), it is the abnormal relationship between the direction of revisions and the return of recommendations, verifying the market reaction by revealing analysts' revisions. It is worth noting that the revisions are measured by the percentage variation of the forecast.

The informativity coefficient is measured by beta , as it is calculated by regressing the abnormal returns, of the equation 4, by revisions of each asset and period , according to equation 5. It is worth noting that this work deals with revisions of price forecasts. The higher the beta, the greater the informational effect will be.

$$CMAR_{jt} = \alpha + \beta_{jt}REV_{jt} + \varepsilon_{jt} \qquad (5)$$

4. HYPOTHESES

4.1. Learning through experience and the complexity of the portfolio

The starting point for analysts' learning analysis were through research by Mikhail, Walther and Willis (1997), Jacob, Lys and Neale (1999) and Clement (1999),

performing analyzes based on the experience and complexity of the industry. The models build the relationship between performance metrics and determining variables of experience, the complexity of assets portfolio and the absorption of information by individuals.

Jacob, Lys and Neale (1999), by contrast, argue that the simple and direct association between experience and accuracy is fragile because not all experiences by repetition have significant effect on returns. Therefore, the results by Martinez (2007) present some evidence of these contrapositions in the earnings forecasts of Brazilian firms. As the learning analysis was not part of the central discussion by Martinez (2007), and because of the particularities presented in the Brazilian market we centralized our central hypothesis in the analyst' experience.

In emerging markets it is also possible to observe the experience of associations with accuracy. However, the results by Karamanou (2012) were general, considering several emerging countries in the world. Due to the heterogeneity between countries used in the sample, it was necessary to perform a cross section in Brazil, mainly due to its different economic characteristics to other developing countries that were investigated Chile, Turkey, Thailand, Korea and China.

By using the learn by doing principle used by Mikhail, Walther and Willis (1997), Jacob, Lys and Neale (1999) and Clement (1999), the metrics that we take as a basis in hypothesis 1 from equation 6 were measured as follows: EXPGEN we count the number of previous periods that the analyst issued a forecast; EXPSETOR we count the number of previous periods that the analyst issued a forecast for a particular sector; and, EXPASSET we count the number of previous periods that the analyst issued a forecast for a particular asset. Based on the studies, we expect that increasing experience contributes to a reduction of forecast errors.

H1: Experience in the execution of forecasts contributes to improved accuracy

$$PAFE_{ijt} = \beta_0 - \beta_1 EXPGEN_{ijt} - \beta_2 EXPSETOR_{ijt} - \beta_3 EXPASSET_{ijt} + \beta_4 NSETOR_{ijt} + \beta_5 NASSET_{ijt} + \varepsilon \qquad (6)$$

Regarding the complexity of portfolio, research by Clement (1999), Duru and Reeb (2002) and Hirst, Hopkins and Wahlen (2004) assume that analysts lose quality in their forecasts from the moment the portfolio diversifies. Lobo, Song and Stanford (2012) claim that the increase in expertise in certain companies and sectors helps to improve analysts' forecasts. Hirst, Hopkins and Wahlen (2004) obtained evidence that analysts who follow fewer firms than the average make better forecasting decisions.

Nevertheless, the study by Martinez (2009) failed to observe this effect with respect to earnings forecasts in Brazilian companies. It is worth mentioning that there is no evidence neither for the analysis of this relationship based on target price forecasts. For this reason, we added two metrics of complexity: NSETOR, which refers to the number of sectors that the analyst covered for the period; and NASSET which corresponds to the number of assets that the analyst covered for the period. Based on studies, we expect that the increased amount of sectors and assets that the analyst covers contribute to reducing accuracy and increasing forecasting errors.

In order to find more answers, equation 6 was also analyzed from the perspective of bias. Hypothesis 2, according to equation 7, contributes to verifying that the experience and complexity measures are also associated to the effects of the analyst's pessimistic or optimistic behavior. This association is based on the study by Duru and Reeb (2002), by observing aspects that increased accuracy is associated with the pessimistic bias, to a conservative behavior of the individual.

H2: Experience in the execution of forecasts is associated with pessimism

$$PFE_{ijt} = \beta_0 + \beta_1 EXPGEN_{ijt} + \beta_2 EXPSETOR_{ijt} + \beta_3 EXPASSET_{ijt} - \beta_4 NSETOR_{ijt} - \beta_5 NASSET_{ijt} + \varepsilon \qquad (7)$$

We expect based on research by Duru and Reeb (2002) that the increase of experience is associated with a pessimist behavior. It is assumed that the increase of experience causes the analyst to become more conservative, which contributes to better results. Regarding the complexity of the portfolio, we expect to understand, on an exploratory basis, the effect of diversification.

On the hypothesis 3, equation 8, we insert the discussion on the learning effect on returns achieved from analysts' recommendations. As there is no evidence in Brazil, we used as a basis the research Mikhail, Walther and Willis (2003) who found evidence that the experience did not show association with the returns of the recommendations. We expect for experience not to present significant association in Brazil in relation to returns.

H3: Experience in performing the forecasts does not contribute to abnormal returns

$$CMAR_{ijt} = \beta_0 + \beta_1 EXPGEN_{ijt} + \beta_2 EXPSETOR_{ijt} + \beta_3 EXPASSET_{ijt} - \beta_4 NSETOR_{ijt} - \beta_5 NASSET_{ijt} + \varepsilon \qquad (8)$$

Considering the complexity of the portfolio, we are based on the studies by Clement (1999), Duru and Reeb (2002) and Hirst, Hopkins and Wahlen (2004) who found that analysts lose quality in their forecasts from the moment the portfolio diversifies. Thus, in hypothesis 3, we expect that the metrics related to the complexity of portfolios to hinder obtaining abnormal returns.

4.2. Learning through the use of information

The informativity is the degree to which the revisions of forecasts impact the movement of asset prices. In the analysis by Givoly and Lakonishok (1979), considering an inefficient market, abnormal returns can be observed months after the revisions of forecasts, and this shows that the reaction is not instantaneous. these effects in emerging markets were also found by Moshirian, Ng and Wu (2009), But these evidence indicate that they have a lower degree of informativity.

Little evidence was found considering the forecast prices, and research by Brav and Lehavy (2003) and Asquith, Mikhail and Au (2005) show strong association between revisions of forecasts and market returns. In particular, Brav and Lehavy (2003) found effects of persistent informativity up to six months after the revisions. Despite these persistent signs of these abnormal changes, we observe that these disorders tend to disappear in the long term (GIVOLY; LAKONISHOK, 1979).

In Brazil, considering the profit projections, Martinez (2008) found low informativity evidence, as did Moshirian, Ng and Wu (2009) in emerging markets. Considering that Brazil has increased efficiency, according to Mobarek and Fiorante (2014), it is possible that informativity has changed over time, which motivated us to check their level of information in relation to the target prices in Brazil.

The effect of the revisions on prices seek to verify the analyst's ability to observe changes in previous forecasts. Knowing this, we can see the individual revisions of the actual analyst, as well as the change in consensus forecasts. In contrast, Asquith, Mikhail and Au (2005) refute the association of individual reviews, showing that these effects are only reiterations.

The argument used by Asquith, Mikhail and Au (2005) starts to make sense when we consider the consensus[1] of forecasts. According to Campbell and Sharpe (2009), analysts are anchored in the consensus of their peers. Williams (2013) explain that the anchoring relationship among peers is an over-estimation that individuals do with others. Then there is the possibility that the consensus forecast revision exhibit greater informational effect than analysts' individual revisions.

Recent evidence by Clement, Hales and Xue (2011) show significant effects that the increase of the consensus revisions cause an increase of individual revisions. This result proves that analysts observe revisions of other analysts before submitting their own revisions, and this leads to the hypothesis that the consensus of the revision is more associated with abnormal returns than individual revisions. Based on this discussion, hypothesis 4 investigates the informativity from the perspective of the percentage of revision of the forecasts of analysts individually REV and the percentage of revision of the consensus of forecasts CREV.

H4: The consensus revision is more associated with abnormal returns than with analysts' individual revisions

$$CMAR_{ijt} = \beta_0 + \beta_1 REV_{ijt} + \beta_2 lag(REV_{ijt}, 1) + \beta_3 CREV_{ijt} + \beta_4 lag(CREV_{ijt}, 1) + \cdots \beta_5 REVGRADE_{ijt} + \beta_6 CREVGRADE_{ijt} + \log(VOLM) + \varepsilon \quad (9)$$

To analyze the informational effect between individual revisions and consensus revisions we will use three reference models. Equation 9 verifies the association between the individual revisions REV and the consensus revisions CREV in abnormal market returns CMAR. Considering the possibility of lag, we also use the same variables REV and CREV with 1 lag.

In the research by Asquith, Mikhail and Au (2005), individuals react more intesively when revisions are for less (downgrades), which allows us to assume that these revisions are absorbed differently. Because of this difference between positive reviews (upgrades) and negative revisions (downgrades), we inserted the variables REVGRADE and CREVGRADE, which assume the values of 0 or 1.

[1] The measurement of consensus is the average of all target price forecasts for the last three months from the date of issue.

REVGRADE is a dummy of analysts' individual revisions, in which positive (*upgrade*) corresponds to 0 and negatives (downgrade) to 1, and the CREVGRADE, is a dummy for consensus revisions, in which positive (upgrade) corresponds to 0 and negatives (downgrade) to 1. These controls are based on evidence by Asquith, Mikhail and Au (2005). The control log(VOLM), trading volume of the asset, is justified by the efficiency of results by Bonini *et al* (2010).

Another variable that we use as a proxy for informational effect is the trading volume. Chae (2005), Brown, Crocker and Foerster (2009) and Bamber, Barron and Stevens (2011) explore the argument that the trading volume of a proxy for the informativity in the market. This argument is used from the impact received by the trading volume from a decision on the market. Therefore, we proposed the informativity analysis by regressing the variable □□□□ by the variation of the revisions of price forecasts previously detailed.

Hypothesis 5, in equation 10, use the trading volume as a proxy for informativity, instead of CMAR. As the evidence discussed in hypothesis 4, we expect that the effects of consensus revisions are also more significant than the individual revisions.

H5: The consensus revision is more associated with traded volume returns than with analysts' individual revisions

$$\log(VOLM)_{ijt} = \beta_0 + \beta_1 REV_{ijt} + \beta_2 lag(REV_{ijt}, 1) + \beta_3 CREV_{ijt} + \beta_4 lag(CREV_{ijt}, 1) + \cdots \beta_5 REVGRADE_{ijt} + \beta_6 CREVGRADE_{ijt} + \varepsilon \quad (10)$$

Finally, the third performance metric used to check informational effects was the accuracy. Clement, Hales and Xue (2011) noted the increased accuracy from the increase in analysts' revisions. Thus, hypothesis 6, through equation 11, uses the argument as a way to verify if revisions affect learning for future forecasts. We expect that revisions in general have a positive association with the accuracy.

H6: The consensus revision is more associated with analysts' accuracy than their own individual revisions

$$\mathrm{PAFE}_{ijt} = \beta_0 + \beta_1 REV_{ijt} + \beta_2 lag(REV_{ijt}, 1) + \beta_3 CREV_{ijt} + \beta_4 lag(CREV_{ijt}, 1) + \cdots \beta_5 REVGRADE_{ijt} + \beta_6 CREVGRADE_{ijt} + \varepsilon \quad (11)$$

5. DATA

From Bloomberg® we collected data on asset prices, their forecasts and recommendations of companies pertaining to the register of the BM&FBovespa. It is worth mentioning that these price estimates are held in the months prior to their target. The collection window comprised the years between 2005 and 2013, mainly by continuing research by Martinez (2007, 2008 and 2009) and Saito, Villalobos and Benetti (2008) and for the availability of observations of forecasts.

The selected companies were all those with assets traded on the BM&FBovespa. The list showed the total of 404 companies and 641 stocks. For the sample, only 195 securities of 176 companies had forecasts in the window used. Thus, out the total of 404 companies registered on the BM&FBovespa, only 44% took part in the research. The database with individual forecasts and recommendations resulted in a total of 62,548 observations. In relation to brokers, 75 of the 80 registered on the BM&FBovespa took part in the research, and 569 of the 1,102 registered analysts in the Association of Investment Analysts and Professionals of the Capital Market - APIMEC. Data collection was performed on a daily basis, though, to optimize the relationships, we used monthly averages.

6. RESEARCH METHOD

The hypotheses were investigated using linear models in panel or longitudinal, according to equation 12. Each dependent variable y_{it} of each individual observed i at time t was evaluated by n determinants $X_{it}\beta$, considering, also, specific control variables according to each hypothesis tested. The use of panel models contribute to obtaining higher degree of freedom and increased efficiency of parameters estimation, as well as assisting to observe elements in time, termed as c_i.

$$y_{it} = X_{it}\beta + c_i + \mu_{it} \qquad (12)$$

In a cross-examination, without considering this effect, the component c_i is within the term error u_{it}, reducing the explanation of the dependent variable (BALTAGI, 2008; PETERSEN, 2009; WOOLDRIDGE, 2010). For the analysis of the individual on the panel, we built an indexer from the concatenation between the analyst's identification variable ANALYST and asset identification ASSET, for it is a two-dimensional panel between each i = *analyst&company* in each time period t.

The unbalanced panel is common in this type of study due to the fact that not all companies have price forecasts at all times. As it is not intended to make comparisons between individuals, but to analyze the determinants of the metrics, the panel balancing is not required, avoiding information losses. Nor did we any model to complete the panel due to the large data gap in the first years, which could lead to unrealistic results. The unbalanced panel is justified to contain all market forecasts in the period analyzed (OBRIEN, 1987; SO, 2013).

In using the Ros software, for the most part, the models used presented fixed effect, according to test results of grouped OLS, Breusch-Pagan's Lagrange Multiplier (1980) and Hausman's specification test (1978). Since this is a long panel, the autocorrelation test becomes more rigorous for a more reliable estimate of parameters, therefore the test by Breusch (1978) and Godfrey (1978) served as a basis. The test results of all models presented evidence of serial autocorrelation in residues, as well as the presence of heteroscedasticity. All tests are described in Appendix.

The presence of autocorrelation and heteroscedasticity affect the covariance matrix, causing loss of the models reliability. To resolve this problem, some studies have suggested the use of more robust alternatives, as Clatworthy, Peei and Pope (2007) and So (2013); thus, a simple solution was to estimate the models using robust standard errors corrected for the autocorrelation and heteroscedasticity, proposed by Arellano (1987).

7. DISCUSSION OF RESULTS

7.1. Descriptive statistics

For the analysis, each performance metrics was analyzed for its descriptive statistics, according to Table 1. In the first analysis, price forecasts have shown on average, with an optimistic bias, considering an average PFE at -0.70, including a minimum of -117.85 points and a maximum of 0.95.

This observed optimism exceeds the results by Schipper (1991); Dreman and Berry (1995); Conroy and Harris (1995); Brown (1996); and Beaver (2002) in the North American market, as well as Martinez (2007) in Brazil, considering earnings forecasts. The individual bias showed more optimism that the results of the consensus bias de -0.41.

The accuracy PAFE was demonstrated around 0.83 points, above the average by Hilary and Hsu (2013) and Bradshaw, Brown and Huang (2013) in the North American market and by Bonini *et al.* (2010) and Kerl (2011) in European markets. Individual errors presented less accuracy than the results of bias consensus 0.53, and this result confirms the argument by Givoly and Lakonishok (1984) that the consensus forecast errors are lesser.

The standard deviation was also greater individually, showing less consistency of forecasts, even in comparison with other markets. The annual returns resulting from the recommendations CRR resulted in a cumulative average of 6% and an average premium of 3% above the market CMAR. The annual consensus returns were also higher, with average CRR at 13% and average CMAR at 6%.

The variable EXPGEN shows that, in general terms, analysts have obtained an average of 2.5 years of experience, compared to 6.5 years in the North American market. Experience with assets resulted in an average of 1.2 years, compared to 3 years in the North American market. The results reflect a less experienced market compared to other more developed ones (YU, 2000).

The average number of sectors in the portfolio of analysts was around 3 segments. The average number of assets in the portfolio analysts was around 6 stocks, compared with latest averages of 14 in the North American market. Thus, the results show evidence that the number of sectors is less diverse than the number of assets. This result shows that analysts in Brazil still cover less assets in

Table 1. Descriptive Statistics.

Metrics	Mean	Standard Deviation	Median	Minimum	Maximum	Amplitude
PFE	-0.70	2.75	-0.20	-117.85	0.95	118.80
PAFE	0.83	2.72	0.30	0.00	117.85	117.85
REV	0.01	0.21	0.00	-0.96	22.73	23.69
CREV	0.01	0.17	0.00	-0.70	6.16	6.86
CRR	0.06	0.47	0.00	-0.97	30.65	31.62
CMAR	0.03	0.45	0.01	-1.70	30.72	32.42
EXPGEN	30.68	22.16	26.00	0.00	95.00	95.00
EXPSETOR	79.77	99.77	43.00	0.00	716.00	716.00
EXPASSET	14.76	14.65	10.00	0.00	154.00	154.00
NSETOR	2.98	2.92	2.00	0.00	16.00	16.00
NASSET	6.01	5.51	5.00	0.00	46.00	46.00

PFE is the percentage of the analyst's forecast error. PAFE is the absolute percentage of the analyst's forecast error. REV is the percentage of forecast variation. CREV is the percentage variation of analysts' consensus forecast. CRR is the cumulative return of the analyst's recommendation. CMAR is the cumulative return of the analyst's recommendation adjusted to the market. EXPGEN is the number of prior forecasts periods that the analyst issued as a whole. EXPSETOR the number of prior forecast periods that the analyst has issued on a particular sector. EXPASSET is the number of prior forecasts periods that the analyst issued on a particular asset. NSETOR is the number of sectors that the analyst issued forecast in the period. NASSET is the number of assets that the analyst issued forecast in the period. All means were significant at 99% confidence.

the portfolio, possibly due to the lower amount of assets in the market (MCNICHOLS; O'BRIEN, 1997; BARTH; KASZNIK; MCNICHOLS, 2001).

7.2. Evolution in time

To analyze the evolution over the years, it was possible to extract the current means of the variables used in the study, and Table 2 shows this extract. The bias over time changes according to the economic instability in the market, with excesses during the economic crisis in 2008 of -1.68. The explanation for this behavior is that possibly, analysts have not considered the impact of the crisis in the Brazilian market, which creates excessive optimism and consequently greater PAFE forecast errors.

In the period of crisis, individual and consensus reviews became negative, which shows the attempt to contain errors in the period. The reduction of individual and consensus revisions in the last three years 2010-2011-2012 possibly affected the accuracy, causing the errors to increase over recent years. This initial result shows the weakness in the accuracy of analysts, especially with the argument by Saito, Villalobos and Benetti (2008) on the low use of more sophisticated statistical techniques in this market.

In addition to accuracy, the cumulative returns of the recommendations were not as significant in the last three years, obtaining returns of 1%, 3% and 4% respectively. Nonetheless, there was a significant improvement in adjusted returns, consequently due to the decline in the market. This shows that returns of recommendations are not always associated with improved accuracy, also observed by Lim (2001).

It was also possible to observe that both the experience and complexity of the portfolio in general, by asset and by sector, increments obtained over the years. The overall experience increased to 3.2 years, with the asset to 1.6 years and 10 years in the industry. This result shows that in Brazil, analysts remain always focused on a particular industry, alternating only the target asset in their portfolio.

The number of reports issued by analysts has grown considerably, as well as the average number of assets in the portfolio, which reached eight stocks. The average number of sectors that the analyst covers was close to four segments. Thus, despite the increase in coverage and issued reports, accuracy has been reduced in recent years, showing possible evidence that growth in the number of reports does not match the improvement in the quality of the results.

7.2. Correlation matrix

As the variables present evidence non-linearity for the development of correlations, we used the Spearman's correlation between the variables. Regarding the result of the matrix, we obtained few strong and significant correlations. They were considered weak below 0.3, medium till 0.6, and strong above 0.6. Based on these criteria, we highlight the main relationships found.

The result of the matrix demonstrates, firstly, an inverse relationship between the bias PFE and the accuracy PAFE of -0.7. The Association presented confirms that the increased pessimism possibly causes a more conservative behavior in the individual, contributing to the increase in accuracy. This conservative effect also presented evidence of a positive association with returns from the recommendations CRR of 0.44. This result explains that analysts who get more returns are more conservative in their forecasts.

Table 2. Annual Means of Variables.

Period	N	PFE	PAFE	REV	CREV	CRR	CMAR	EXPGEN	EXPSETOR	EXPASSET	NSETOR	NASSET
2005	2017	0.04	0.27	0.01	0.00	0.21	-0.15	5.48	8.36	4.21	1.33	3.11
2006	3060	0.00	0.27	0.03	0.06	0.16	-0.15	14.15	23.45	9.04	1.66	3.61
2007	4502	-0.79	0.89	0.03	0.05	-0.07	-0.14	18.44	30.67	9.42	1.92	4.35
2008	7163	-1.68	1.73	-0.02	-0.01	0.02	0.01	23.56	44.34	11.07	2.31	5.04
2009	7884	-0.08	0.35	0.03	0.01	0.26	-0.03	27.47	63.44	13.20	2.73	5.19
2010	10888	-0.50	0.60	0.02	0.02	0.01	0.08	32.55	83.68	14.43	3.07	5.83
2011	12843	-0.67	0.77	0.00	0.00	0.03	0.05	36.96	102.29	17.47	3.41	6.59
2012	14191	-0.94	1.07	0.01	0.00	0.04	0.12	39.95	121.22	19.72	3.88	8.04

PFE is the percentage of forecast error. PAFE is the absolute percentage of forecast error. REV is the percentage variation of individual forecast of analysts. CREV is the forecast's percentage variation of analysts' consensus. CRR is the cumulative return of the recommendation. CMAR is the cumulative return of the adjusted recommendation to the market. EXPGEN is the number of previous forecasts that the analyst issued. EXPSETOR the number of previous forecasts that the analyst has issued on a particular sector. EXPASSET is the number of previous forecasts that the analyst issued for a particular asset. NSETOR is the number of sectors that the analyst issued forecasts in the period. NASSET is the number of assets that the analyst issued forecasts in the period.

Another important highlighted association is that the increase of accuracy is not directly associated with the increase of the recommendations returns. PAFE presented an association of -0.46 for CRR and -0.28 for the CMAR. This result corroborates with Lim (2001), for whom accuracy will not always reflect in positive returns due to conflicts that may occur between estimates and recommendations by the actual analyst. The explanation for this association is that, at times, the analyst changes their recommendation even if not in accordance to their own forecast, due to informational asymmetry.

Finally, other relationships observed showed only minor associations. The independent variables, experience and complexity of the portfolio showed significant relationships with each other, presenting collinearity. However, the models used in panel are not affected because of multicollinearity (BALTAGI, 2008).

7.3. Analysis of learning through experience and complexity of the portfolio

Table 4 shows the evaluation results of the analysts' experience and the complexity of the portfolio. The first results are of hypotheses 1, 2 and 3 associated with the learning of the analyst, with both the accuracy as with the bias and the returns of the recommendations. The log(VOLM) control, which is the trading volume of assets in the period, has been previously used by Bonini et al (2010).

Based on the study by Asquith, Mikhail and Au (2005), the variable REVGRADE was inserted to control the imbalance between revisions for less (downgrades) and revisions for more (upgrades). This control shows that investors react more significantly when reports show revisions for less (downgrades).

Due informational asymmetry control purposes, we calculate the so-called variable CONFLICT; this dummy variable is classified with 1 when there is conflict to the rule according to Bradshaw (2002) between the forecast and the recommendation and 0 when the rule is followed and there is no conflict. Informational asymmetry comes from the imbalance between the indication of the forecast and the analyst's recommendation. Another control variable was the variation of the Bovespa index, and this choice was made due to the change in the market in 2008; probably because of the economic crisis, the IBOV variable tries to control the effects of the economic movement.

Regarding the results observed in Table 4, increased experience with the sector and the increased experience with the asset demonstrated concordance with increased accuracy and are associated with a pessimistic behavior, strengthening the evidence by Mikhail, Walther and Willis (1997) and Mikhail, Walther and Willis (2003). This relationship demonstrates that experience with certain segments and assets contributes over repeated exercise to achieve better target price forecasts.

Table 3. Correlation matrix.

	PFE	PAFE	REV	CREV	CRR	CMAR	EXPGEN	EXPSETOR	EXPASSET	NSETOR
PFE										
PAFE	-0.70***									
REV	0.02***	-0.03***								
CREV	0.15***	-0.16***	0.13***							
CRR	0.44***	-0.46***	0.00	0.00						
CMAR	0.23***	-0.28***	0.01**	0.06***	0.70***					
EXPGEN	-0.02***	-0.02***	-0.01**	-0.04***	-0.01*	0.11***				
EXPSETOR	-0.01**	-0.05***	-0.01***	-0.05***	0.00	0.10***	0.86***			
EXPASSET	0.01*	-0.04***	0.00	-0.05***	-0.02***	0.07***	0.63***	0.74***		
NSETOR	0.00	-0.08***	-0.04***	-0.01***	0.01***	0.08***	0.27***	0.39***	0.16***	
NASSET	-0.01*	-0.04***	-0.03***	-0.01***	0.01	0.11***	0.38***	0.33***	0.15***	0.61***

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
PFE is the percentage of forecast error. PAFE is the absolute percentage of forecast error. REV is the percentage variation of individual forecast of analysts. CREV is the forecast's percentage variation of analysts' consensus. CRR is the cumulative return of the recommendation. CMAR is the cumulative return of the adjusted recommendation to the market. EXPGEN is the number of previous forecasts that the analyst issued. EXPSETOR the number of previous forecasts that the analyst has issued on a particular sector. EXPASSET is the number of previous forecasts that the analyst issued for a particular asset. NSETOR is the number of sectors that the analyst issued forecasts in the period. NASSET is the number of assets that the analyst issued forecasts in the period.

On the other hand, as according to Martinez (2007), the overall experience showed negative effects with accuracy, refuting Mikhail, Walther and Willis (2003). It is possible that in Brazil, for the counting of these issued reports to be biased due to informational asymmetry from the difference between forecast and recommendations. Somehow, a junior analyst with lower reputation, has no discretional power to bias their estimates, unlike a senior analyst who incurs in intentional bias. If the increase of issued reports are confrontational, as shown in Table 2, it can explain the reason for this contradictory relationship to learning through repetition.

In relation to the complexity of the analyst's hedging portfolio, the results presented significant association for both of the variables NASSET and NSETOR. The variable NSETOR confirms the evidence by Jacob, Lys and Neale (1999), Duru and Reeb (2002), Hirst, Hopkins and Wahlen (2004) and Lobo, Song and Stanford (2012) that the increase in the number of sectors is related to the increase in forecast errors and, consequently, associated with reduced accuracy.

In contrast, the NASSET variable indicated that the increase in the number of assets is linked to improving accuracy and reducing errors, this effect is contradictory to the results by Jacob, Lys and Neale (1999). It is possible that, in Brazil, the analysis of assets within the same sector has a beneficial association due to the lower amount of traded assets on the BM&FBovespa and in the portfolios of analysts.

All control variables showed significant results in the analysis of performance metrics. We highlight the variable CONFLICT, which represents part of the informational asymmetry between analysts and

Table 4. Experience and Complexity

Hypotheses	1	2	3
Dependent Variable	PAFE	PFE	CMAR
EXPGEN	0.011***	-0.011***	0.0001
	(0.001)	(0.001)	(0.0001)
EXPSETOR	-0.002***	0.003***	0.00002
	(0.0003)	(0.0002)	(0.00004)
EXPASSET	-0.002*	0.002*	-0.0003
	(0.001)	(0.001)	(0.0002)
NSETOR	0.038***	-0.044***	-0.001
	(0.005)	(0.005)	(0.001)
NASSET	-0.027***	0.028***	-0.001
	(0.003)	(0.003)	(0.001)
log(VOLM)	0.223***	-0.227***	-0.011**
	(0.045)	(0.045)	(0.004)
CONFLICT	-0.371***	0.565***	-0.118***
	(0.053)	(0.050)	(0.043)
IBOV	-2.892***	3.056***	-0.374***
	(0.249)	(0.258)	(0.049)
REVGRADE	0.161**	-0.144**	0.005
	(0.063)	(0.066)	(0.011)
EXPGEN: CONFLICT	0.004***	-0.004***	0.004***
	(0.002)	(0.001)	(0.002)
EXPSETOR: CONFLICT	0.0004*	-0.001***	-0.0004*
	(0.0002)	(0.0002)	(0.0002)
EXPASSET: CONFLICT	-0.004*	0.004**	-0.005***
	(0.002)	(0.002)	(0.001)
NSETOR: CONFLICT	0.007	-0.010	0.018***
	(0.010)	(0.011)	(0.004)
NASSET: CONFLICT	-0.005	0.003	0.004**
	(0.005)	(0.006)	(0.002)
Observations	62,006	62,006	62,006
R^2	0.030	0.032	0.011
Adjusted R^2	0.029	0.032	0.011

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

PAFE is the absolute percentage of forecast error. PFE is the percentage of forecast error. CMAR is the cumulative return of the adjusted recommendation to the market. EXPGEN is the number of prior forecasts periods that the analyst issued as a whole. EXPSETOR the number of previous forecasts that the analyst has issued on a particular sector. EXPASSET is the number of previous forecasts that the analyst issued for a particular asset. NSETOR is the number of sectors that the analyst issued forecasts in the period. NASSET is the number of previous forecasts that the analyst issued for a particular asset. log(VOLM) is the logarithm of the asset's trading volume. CONFLICT is a dummy representing the contradictory effect between the forecast and the recommendation of the analyst, with 1 when there is conflict, and 0 when there is none. REVGRADE is a differentiation dummy of the revisions for less (downgrade) 1 and for more (upgrade) 0.

investors. The variable was also significant from the interactions between the experience and accuracy metrics and demonstrates that analysts' reports in Brazil need to be less conflictive and have more technical rigor.

Regarding hypothesis 3, there were some significant effects pointing that experience is associated with the recommendations returns, but only when these experiences are disassociated from forecasts. Although small, the EXPGEN showed that increasing the overall experience is positively related to the increase of abnormal returns and that the increase in EXPASSET is negatively associated with increasing returns. This observed relationship refutes the results by Mikhail, Walther and Willis (2003that experience is not related to returns. In other words, when there is informational asymmetry, experience and complexity of the portfolio distort the effects of the learn by doing assumptions.

7.4. Learning analysis by informativity

The results of Table 5 show the correlations in the hypotheses of informativity. The first model of the hypothesis 4, demonstrates a significant association of analysts' abnormal returns in relation to consensus revision, which was not observed with the individual revisions. The positive relationship confirms the anchoring that individuals place on their peers, reinforcing evidence by Campbell and Sharpe (2009) and Williams (2013). Considering the increase in reports and conflicts between forecast and recommendations, it is possible to assume that in some cases analysts are only replicating previous reports of their peers.

Despite evidence of increased efficiency in the Brazilian market Mobarek and Fiorante (2014), the association between consensus review and abnormal returns persists even for a lag, confirming the argument by Givoly and Lakonishok (1979) and Brav and Lehavy (2003) of persistence of the informational effect. The weak informativity in the market also confirms the research by Martinez (2008) and Moshirian, Ng and Wu (2009). However, based on the informativity of the consensus revisions, it is possible to obtain abnormal earnings observing the movements of these revisions in the Brazilian market.

Regarding the model's weakness of the hypothesis 5, the trading volume did not present a good proxy to analyze the market's informational effect. The result meets the variable defended by Chae (2005), Brown, Crocker and Foerster (2009) and Bamber, Barron and Stevens (2011). Possibly, revisions and changes in price forecasts alter the shape of companies' value and do not create incentives to increase the trading volume.

In considering hypothesis 6, the effect of informational consensus revisions intensifies the impact on returns when revisions are for less (downgrades) confirming the evidence by Asquith, Mikhail and Au (2005). Hypothesis 6 shows that the analysts' consensus revisions CREVGRADE are undermining target price forecasts and therefore, it explains the adverse relationship in preliminary abnormal returns.

The result of the association of the consensus confirms the hypothesis that analysts point out anchoring moments on their peers and corroborates the argument by Williams (2013) that individuals are anchored on the similarities of their peers to issue their recommendations. However,

Table 5. Informativity

Hypotheses	4	5	6
	CMAR	log(VOLM)	PAFE
REV	0.074 (0.056)	-0.014 (0.104)	-0.254 (0.193)
lag(REV, 1)	0.024 (0.039)	0.276 (0.194)	-0.206 (0.262)
CREV	-0.174*** (0.044)	-0.036 (0.207)	-0.235 (0.800)
lag(CREV, 1)	-0.162*** (0.055)	-0.005 (0.166)	-0.541 (0.402)
REVGRADE	0.052* (0.028)	0.024 (0.068)	0.235 (0.188)
CREVGRADE	-0.056*** (0.007)	0.366*** (0.052)	0.456*** (0.074)
log(VOLM)	-0.020*** (0.006)		0.410*** (0.069)
CONFLICT	-0.013 (0.025)	-0.209*** (0.025)	-0.288*** (0.045)
IBOV	-0.585*** (0.058)	-0.171 (0.129)	-2.480*** (0.353)
Observations	23.668	23.668	23.668
R^2	0.015	0.017	0.044
Adjusted^{R2}	0.015	0.017	0.044

Note: *p < 0.1; **p < 0.05; ***p < 0.01.
CMAR is the cumulative return of the recommendation adjusted to the market. log(VOLM) is the logarithm of the asset's trading volume. PAFE is the absolute percentage of forecast error. REV is the percentage of the expected price revision by the analyst. lag(REV,1) is the percentage of the expected price revision by the analyst lagged by one period. CREV is the percentage of the expected price revision by consensus. lag(CREV,1) is the percentage of the expected price revision by consensus lagged by one period. REVGRADE is a differentiation dummy of analysts' individual revisions between the negative (downgrade) 1 and positive (upgrade) 0 variation. CREVGRADE is a differentiation dummy of analysts' consensus revisions between the negative (downgrade) 1 and positive (upgrade) 0 variation.

the negative association with the returns and the positive association with the errors, show that this anchoring is damaging to the activity.

8. FINAL CONSIDERATIONS

In this study, we explored the association between learning, the complexity of the hedging portfolio and the informativity in target price forecasts and recommendations of sell-side analysts considering the informational asymmetry on the BM&FBovespa. The variables demonstrated that the Brazilian market presented optimism and excessive errors compared to other markets such as the North American.

Revisions by individual analysts presented associations with analysts' consensus, which confirmed the argument of anchoring on their peers by Campbell and Sharpe (2009) and Williams (2013). The possible explanation for this association is that, the accuracy of consensus forecasts was greater than the individual accuracy. Whereas the average presents better results, analysts seek to observe their peers in order to conduct new analyses. As an example, the award of the returns of consensus recommendations were 6% per annum compared to 3% by analysts individually.

With regard to learning, the overall experience was 2.5 years, much lower than the 6.5 years of the North American market, as well as the experience with each asset being 1.2 years, much lower than 3 years, respectively. These results show less experienced professionals than in more developed markets, which explains the lower accuracy.

The average number of sectors in the portfolio of analysts was around 3 segments, with an average of 6 stocks in the portfolio, compared to the average of 14 stocks in a more recent survey in the North American market. This result shows how analysts in Brazil still cover less stocks in the portfolio, possibly due to the lower amount of assets offered in the market.

The increase in experience with sectors and assets, as well as the complexity of the portfolio, confirmed the learn by doing principle in Brazil. But increasing experience in general presented a hindering effect on accuracy due to the observed informational asymmetry. The result of this distortion are the positive recommendations returns, but defected target price forecasts.

One possible conclusion is that more experienced analysts in the market, with greater discretionary power, prefer to change their recommendations, contradicting their own target price forecasts in an attempt to intentionally bias the market. Thus, less experienced analysts cannot cause such effect, but their lack of abilities and the low use of more sophisticated statistical models reduce its accuracy with assets and sectors, confirming the argument by Saito, Villalobos and Benetti (2008).

To solve the observed bias, we suggest formulating analysts' classification that are more objective, less biased and who value good analysis, reinforcing the argument by Emery and Li

(2009). Existing rankings in the Brazilian market should encourage the elimination of possible contradictions between forecasts and recommendations, enabling the increase in the quality of analysis results.

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APPENDIX A. Statistical Tests of Models in Panel.

Table A1. Statistical Tests of Panel in Models.

Hypothesis	Test 1	Test 2	Test 3	Test 4	Test 5
1	520970000	19.151	3988.1	417.69	71806
sig.	***	***	***	***	***
2	521700000	20.539	8428.5	431.79	69535
sig.	***	***	***	***	***
3	693160000	13.298	66.6	301.6	123410
sig.	***	***	***	***	***
4	190450000	4.6524	72.511	31.027	49491
sig.	***	***	***	***	***
5	475990000	3.3982	39.036	36.116	452.19
sig.	***	***	***	***	***
6	670380000	2.5054	34.392	19.931	55581
sig.	***	***	***	***	***

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

The tests applied in the models of consensus analysis were (1): Lagrange's Multiplier Test-time effects (Breusch-Pagan), (2) F test for individual effects, (3) Hausman's test, (4) Breusch-Godfrey's test for serial correlation in panel models, and (5) Breusch-Pagan's test for heterocedasticity.