FUNDAÇÃO INSTITUTO CAPIXABA DE PESQUISAS EM CONTABILIDADE, ECONOMIA E FINANÇAS - FUCAPE

DANILO SOARES MONTE MOR

THE ROLE OF ACCOUNTING FUNDAMENTALS AND OTHER INFORMATION ON STOCK PRICES AND ANALYST FORECAST ERRORS

VITÓRIA
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Tese apresentada ao Programa de Doutorado em Ciências Contábeis e Administração da Fundação Instituto Capixaba de Pesquisas em Contabilidade, Economia e Finanças - Fucape, como requisito parcial para obtenção do título de Doutor em Ciências Contábeis e Administração de Empresas.

Orientador: Prof. Dr. Fernando Caio Galdi.

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VITÓRIA
2014

EPÍGRAFE

“All Models Are Wrong, But Some Are Useful”

George E.P. Box

DEDICATÓRIA

Aos meus pais Luzia, que amo muito, e Izailton, o melhor pai que um filho pode ter, e ao nosso JESUS CRISTO, que me emprestou seu colo nas horas de aflição.

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RESUMO

Ohlson (1995), ao derivar uma relação que estabelece um link entre informações observáveis e expectativas de lucro, demonstra que o valor intrínseco da firma pode ser expresso a partir de uma função linear que considera, além de dados contábeis contemporâneos, “outras informações relevantes” ainda não presentes nas demonstrações contábeis, mas que ainda devem impactar os lucros. No nosso primeiro artigo, com base na hipótese de que as projeções dos analistas contém informações representando expectativas dos investidores acerca dos lucros futuros, nós investigamos se os preços das ações têm refletido as informações contidas nas projeções dos analistas de acordo com a associação dessas informações com os lucros do final do ano fiscal. Nossos resultados apresentam evidências de que o mercado não precifica corretamente as outras informações contidas nas projeções dos analistas, e também falha em precificar o impacto apropriado de notícias boas e ruins nos lucros futuros. Nós também apresentamos evidências de que o mercado sobreprecifica as outras informações propiciando oportunidades de arbitragem, que são ainda maiores quando o impacto esperado das outras informações é suficientemente grande e os analistas têm consenso com relação à tais impactos.

No nosso segundo artigo nós implementamos uma abordagem que nos permite estimar a extensão em que os erros dos analistas estão relacionados à informações contábeis e à outras informações. Nossas análises levam à duas conclusões: primeiro, analistas não são necessariamente nem otimistas e nem pessimistas: isso depende do tipo, do sinal e da magnitude da informação. Segundo, previsões acuradas podem ser feitas até mesmo quando estão associadas à grandes erros de previsão negativos das outras informações e grandes erros de previsão positivos das informações contábeis. Em outras palavras, até mesmo quando os analistas estão certos, eles podem estar errados. Nesses casos, nossos resultados sugerem que a sorte supera a habilidade.

No terceiro artigo, nós apresentamos uma abordagem alternativa que nos permite derivar as outras informações direto dos preços das ações ao invés do consenso dos analistas. Uma vez que o preço das ações, sob as hipóteses de Ohlson (1995) e eficiência de mercado, refletem completamente todas as informações disponíveis, nossa proxy para outras informações pretende mitigar o viés de previsão presente na literatura atual. Enquanto verificações empíricas ainda são necessárias, nossa análise teórica revela uma solução implícita para os parâmetros de persistência da dinâmica de informação e uma proxy para as outras informações que satisfazem as hipóteses de Ohlson (1995).

Palavras-Chave: Fundamentos Contábeis; Outras Informações; Anomalias de Mercado; Erros dos Analistas.

ABSTRACT

Ohlson (1995), by deriving a relation that links observable information with expectation of future earnings, demonstrates that the firm's intrinsic value can be expressed as a linear function of contemporaneous accounting data and "other relevant information" not yet accurate in the financial statement, but that have yet to have an impact on earnings. In our first paper, based on the assumption that analyst forecasts contain information representing investors' current expectation of future earnings, we analyse whether stock prices fully reflect other information contained in analysts' forecasts according to its association with one-year-ahead earnings. Our results present evidences that the market does not correctly price other information contained in analysts' forecast, and also fails to price appropriately the impact of good and bad news on future earnings. We also provide evidences that the market overprices other information leading to arbitrage, which is larger when the expected impact of such information on future earnings is sufficiently large and analysts agree about it.

In our second paper we implement an approach that allow us to disaggregate analyst forecast errors into an error related with past accounting information and another error related with other information, in order to evaluate the extent in which analyst forecast errors are associated with information from these two different sources. Our analyses lead to two conclusions: first, analysts are neither optimistic nor pessimistic: it depends on the type, the sign, and the magnitude of the information. Second, accurate forecasts can be done even when it is associated with large positive accounting errors and large negative other information errors. In other words, even when analysts are right, they might be wrong. In these cases, our results suggest that luck trumps skills.

In our third paperwe present an alternative approach that allow us to derive other information directly from stock prices instead from consensus analyst forecasts. Since price of equity, under Ohlson's (1995) assumptions and market efficiency, fully reflects all public information, our proxy for other information intends to mitigate the forecast bias present in the current literature. An advantage of our approach is that it is based on the variables contained on the Linear Information Dynamic, and no further assumption is required.Our theoretical analysis reveals an implicit solution for the persistence parameters of the information dynamic and a proxy for other information that satisfy Ohlson's (1995) assumptions.

Keywords: Accounting Fundamentals; Other Information; Market Anomaly; Analyst Forecast Errors.

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1 INTRODUCTION

Edwards and Bell (1961) and Peasnell (1982) show that, by assuming only clean surplus relation, a firm's intrinsic value can be obtained by the sum of book value and the present value of expected future abnormal earnings (Residual Income Valuation Model - RIV). This inherent accounting appealing, however, is not sufficient to implement RIV, since expectations are unobservable and RIV is a function of expectations (Myers, 1999). Ohlson's (1995) contribution comes from the modeling of the Linear Information Dynamic[1] (LIM), which allows expected future earnings to be expressed as a function of contemporaneous accounting data, and other relevant information.

In a practical perspective, other information can be interpreted as all new information not yet accurate in the financial statement, but that have yet to have an impact on earnings. A discovery of a new petroleum field, new patents, regulatory approval of a new pharmaco, new long-lived contracts, a CEO's death, among others, can be seen as obvious candidates for other information (Myers, 1999). The term other information, indeed, is theoretically designed to summarize value relevant events that have yet to have an impact in the financial statements, bearing upon future (abnormal) earnings independently of past (abnormal) earnings. Since these events impact earnings as opposed to the persistence of past earnings, there is a time-delay by the accounting measures to incorporate these value relevant information. This is one of the motivation for considering other information beyond earnings, book value, and dividends in valuation models.

Some studies attempt to investigate how stock prices react to other information. Salas (2010), for example, investigates stock prices reaction to sudden executive deaths[2]. Salas argues that "if a highly effective manager dies unexpectedly, the stock price reaction should be negative" (as happened with Apple's stock price after Steven Jobs's death)... "If however [the] death removes an entrenched manager when the board would or could not, the stock price reaction should be positive"[3] (Salas, 2010). Other studies including Kaplanski and Levy (2010) investigate the consequences of aviation disasters on stock prices. They find that these events are associated with an average market decline of more than $60 billion per accident[4]. These news represent only few examples among an infinite number of other information that may affect firm's future performance and investors' expectations of firm's future performance.

From an empirical point, some studies have already used information contained in analysts' forecast as proxy for other information, based on the assumption that analysts' forecast contain information representing investors' current expectation of future earnings[5]. As analysts' forecast depend on information

[1]The goal of the information dynamic is that it allows us to obtain a linear pricing solution in function of accounting information and other information, and only three accounting variables are required to summarize the accounting component. According to Rubinstein (2006), this approach of linking future information determining present value to current information can be viewed as a more sophisticated version of Willians' (1938) perpetual dividend growth model, and is an important contribution to subsequent empirical research by reorienting the way that accounting data is used to explain stock prices.

[2]Etebari et al. (1987) find a negative reaction to sudden executive deaths. Worrell et al. (1986) find that firms on average experience negative abnormal returns when the CEO dies, but positive if the death is related to the chairman of the board.

[3]These arguments surrounding an executive's death and a board turn over are consistent with evidences in Denis and Denis (1995) suggesting that investors' attitudes towards executives is a function of performance.

[4]Marketing science has long acknowledged the effect that feelings provoked by disasters have on advertisement's effectiveness (Hoffman and Oliver-Smith 1999, Hill 2002, 2005, Cardona 2004). According to this literature, emotions have important influences on consumers' beliefs about brands' attributes, perceived risk, and also on the consumption level.

[5]According to a study developed by researchers of University of Michigan based on more than 470,000 analyst reports and 18,000

contained in past earnings and book value, Dechow et al. (1999) use the abnormal component of analysts' forecast as proxy for other information, where the persistence parameter of abnormal earnings is estimated in a first-stage regression. In contrast, Brian and Tiras (2007) use the regression residual of consensus analysts' forecast on earnings and book value as proxy for other information.

In this work we address three issues according to other information: First, although market anomalies relating current earnings components to future earnings is frequently explored in the literature (Sloan 1996, Xie 2001, etc.), the market assessment of the impact of "other" information on future earnings have not yet received due attention under a market efficiency point of view. Whether or not the market is efficient according to other information is an issue that still requires empirical verification.

To test whether stock prices fully reflect the impact of other information contained in analysts' forecast on earnings, a specification of a "naive" expectation model is necessary, against which to test the null hypothesis of market efficiency. A parsimonious naive model applied to this situation is that the market prices the persistence of earning components and the impact of other information on earnings, but fails to price the appropriate impact of good and bad news on earnings. As measure of other information, we use the proxy suggested by Brian and Tiras (2007). Following Sloan (1996) and Xie (2001), we use the Mishkin test (1983) and the hedge-portfolio test to access this issue.

The framework of the Mishkin (1983) test starts from the basic implication that, conditional on a set of information, in expectation, abnormal returns are zero under market efficiency. If the market correctly anticipates the impact of other information contained in analysts' forecast of one-year-ahead earnings, then the market's valuation coefficient of other information should be statistically equal to the coefficient that relates this information with one-year-ahead earnings. On the other hand, if the coefficient relating current information to future earnings is not proportional to the coefficient relating that information to returns, then the null will be rejected. Since the forecasting coefficient is a measure of the average impact of other information on earnings, we attribute any mispricing of other information contained in analysts' forecast to the market's failure to correctly weigh this information according to its impact on earnings.

Second, several results in the literature raise concerns about the incentive misalignment between analysts and investors, and present evidences that analysts are generally optimistic and produce biased forecasts (Brown, Foster and Noreen (1985), Stickel (1992), Abarbanell (1991), Stickel (1998), Das, Levine and Sivaramakrishnan (1998), Lin and McNichols (1998), Michaely and Womack (1999), Dechow, Hutton, and Sloan (2000), and Cowen, Groysberg and Healy (2006)). The literature, however, have not yet investigated how biased analysts are according to other information. Whether or not analysts fully reflect other information according to its association with earnings is another issue that requires empirical verification.

In order to identify and test how accurate analysts are in processing other information, we developed a methodology that disaggregate analyst forecast errors into an error related with past accounting information and another error related with other information. Our analyst error disaggregation approach fundamentally is based on the assumption that, conditional on a set of available accounting information and other information, in expectation, consensus analyst forecast errors should be zero (Unbiased Forecast

conference call transcripts, "financial analysts highlight information in reports that aren't mentioned on calls with corporate officers and flesh out issues given just brief mentions on the calls" (University of Michigan, 2014). "this finding suggests that analysts frequently provide new information by discussing exclusive topics that were not referred to in the CC" (Allen Huang et al., 2014).

Condition - UFC).

By considering the unbiased forecast condition, if analysts on average correctly forecast the persistence of earnings components, book value, and dividends, then the coefficients relating these accounting components to analysts' expectation of next year earnings should be proportional to the coefficients relating these components to next year earnings. But if we reject the null for any of these variables, then it would suggest that analysts do not fully incorporate the persistence of the respective component into their forecast. On the other hand, if analysts on average correctly forecast the impact of other information on future earnings, then analysts' expectations about the impact of other information on next year earnings and the realized impact of other information on next year earnings should be statistically equal. If we reject this null hypothesis, it would suggest that analysts do not fully forecast the impact of other information on earnings.

Third, once analysts may forecast earnings with bias, estimate other information directly from consensus analysts forecast could cause an estimation bias. In this work we present an alternative approach that allow us to derive other information directly from stock prices instead from consensus analyst forecast, With this approach, we intend to mitigate the forecast bias present on the current methodologies that are directly affected by analysts' incentives to issue biased forecasts.

In summary, we find that:

1. First, as expected, other information are positively correlated with current returns and size-adjusted abnormal returns, and also with earnings, but are not correlated with past earnings. Moreover, the results of the Mishkin test suggest that the market acts as if it on average underprices the impact of good news and overprices the impact of bad news on earnings, which is consistent with the assumption that the market gives on average more weight for bad news than for good news. A non linear analysis, however, reviews that the market tends also to overprice the impact of positive other information when the expected impact of this information on earnings is sufficiently large. Consistent with this result, the lowest (highest) decile portfolios experience positive (negative) size-adjusted abnormal returns in the year after the portfolio formation. At this point, the hedge portfolio generates positive and significant returns and support the overpricing of extreme other information, as suggested by the non-linear Mishkin test. Further analysis also find that these abnormal returns are even larger for portfolios formed by firms-year that belong to information environments with low analyst forecasts dispersion. In general, our results suggest that the market misprices other information leading to arbitrage, which is larger when the expected impact of this information on earnings is sufficiently large and analysts agree about it.

2. Second, in spite of some similarities among our descriptive statistics with the widely held beliefs among accounting and finance academics about analysts generally producing optimistic forecasts, analyses associated with the distribution of forecast errors of other information raises doubts about this conclusion. In our analyses, far more extreme other information (accounting) forecast errors of greater magnitude are observed in the ex-post "pessimistic" ("optimistic") tail of the distribution rather than in the "optimistic" ("pessimistic") tail. These characteristics of the distributions of accounting and other information forecast errors suggest that analysts may have different behaviors in forecasting the persistence of accounting data and the impact of new information on earnings.

In the other information dimension, indeed, our results suggest that analysts seem to forecast positive other information not with optimism, but with pessimism, and that analysts are even more pessimistic according to good news in poor information environments, where analyst forecast dispersion is high. According to the persistence of accounting information, we present evidences that analysts are on average optimistic, and that book value, normal accruals, and negative abnormal accruals are together the cause of this partial optimism. In summary, our analyses suggest that accurate forecasts can be done even when it is associated with large positive accounting errors and large negative other information errors. In other words, even when analysts are right, they might be wrong.

3. Finally, in the last chapter we presented the alternative approach that allow us to derive other information directly from stock prices instead from consensus analyst forecast. Since price of equity, under Ohlson's (1995) assumptions and market efficiency, fully reflect all public information, our derivation of other information intends to mitigate the forecast bias present on methodologies that are directly affected by analysts' incentives to issue biased forecasts. Our analysis reveals an implicit solution for the persistence parameters of the information dynamic, which satisfies Ohlson's (1995) assumptions. An advantage of our approach is that only the variables described on Ohlson's (1995) model were required for the estimation procedure.

The remaining of this dissertation is organized as follows. In the next chapter we address the first issue about the market pricing of other information contained in analysts' forecasts. In chapter 3 we introduce our analyst forecast error disaggregation approach in order to verify how biased analysts are according to other information. In chapter 4, we introduce the approach that intends to estimate other information by mitigating the forecast bias present on the current literature. Finally, in chapter 5 we provide a summary and conclusions.

2 ARE STOCK PRICES EFFICIENT TO OTHER INFORMATION CONTAINED IN ANALYSTS' FORECAST?

Abstract

Ohlson (1995), by deriving a relation that links observable information with expectation of future earnings, demonstrates that the firm's intrinsic value can be expressed as a linear function of contemporaneous accounting data and "other" relevant information not yet accurate in the financial statement, but that have yet to have an impact on earnings. Based on the assumption that analysts provide information representing investors' current expectation of future earnings, we analyse whether stock prices fully reflect other information contained in analysts' forecasts according to its association with realized earnings. Our results present evidences that the market is not efficient according to other information contained in analysts' forecast, and also fails to price appropriately the impact of good and bad news on future earnings. We also provide evidences that the market overprices other information leading to arbitrage, which is larger when the expected impact of such information on future earnings is sufficiently large and analysts agree about it.

2.1 INTRODUCTION

The firm's intrinsic value, as showed by Ohlson (1995), can be expressed as a linear function of contemporaneous accounting data and "other" relevant information beyond that reflected by the accounting fundamentals. In a practical perspective, other information can be interpreted as all new information not yet accurate in the financial statement, but that have yet to have an impact on earnings. A discovery of a new petroleum field, new patents, regulatory approval of a new pharmaco, new long-lived contracts, a CEO's death, among others, can be seen as obvious candidates for other information (Myers, 1999).

Some studies in the literature spanning finance, economics and accounting attempt to investigate how stock prices react to other information. Salas (2010), for example, investigates stock prices reaction to sudden executive deaths[6]. Salas argues that a highly effective manager dies unexpectedly, the stock price reaction should be negative" (as happened with Apple's stock price after Steven Jobs's death). If however [the] death removes an entrenched manager when the board would or could not, the stock price reaction should be positive"[7]. Other studies including Kaplanski and Levy (2010) investigate the consequences of aviation disasters on stock prices. They find that these events are associated with an average market decline of more than $60 billion per accident[8]. These news represent only few examples among an infinite number of other information that may affect firm's future performance and investors' expectations of firm's future performance.

In a valuation context, although market anomalies relating current earnings components to future earnings is frequently explored in the literature (Sloan 1996, Xie 2001, etc.), the market assessment of

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the impact of "other" information on future earnings have not yet received due attention under a market efficiency point of view. Whether or not the market is efficient according to other information is an issue that still requires empirical verification.

Studies including Ramnath et al. (2008), Shan et al. (2013), and So (2013) argue that analysts play an important role in capital markets by interpreting public and private information relating to companies, industries, and the economy, and by facilitating the valuation process in translating this mixture of information into forecast of future earnings. According to a study developed by researchers of University of Michigan based on more than 470,000 analyst reports and 18,000 conference call transcripts, "financial analysts highlight information in reports that aren't mentioned on calls with corporate officers and flesh out issues given just brief mentions on the calls" (University of Michigan, 2014). "this finding suggests that analysts frequently provide new information by discussing exclusive topics that were not referred to in the CC" (Allen Huang et al., 2014). Based on these evidences and on the assumption that analysts' forecast contain information representing investors' current expectation of future earnings, this paper analyses whether stock prices are efficient to other information contained in analysts' forecast according to its association with realized earnings.

Some studies have already used information contained in analysts' forecast as proxy for other information. Considering the argument that analysts' forecast depend on information contained in past earnings and book value, Dechow et al. (1999) use the abnormal component of analysts' forecast as proxy for other information, where the persistence parameter of abnormal earnings is estimated in a first-stage regression. In contrast, Brian and Tiras (2007) use the regression residual of consensus analysts' forecast on earnings and book value as proxy for other information. The results found by Bryan and Tiras (2007) initially validate Dechow et al.'s (1999) cross section findings, which generally support Ohlson's (1995) linear information dynamic, but neither Dechow et al. (1999) nor Bryan and Tiras (2007) investigate whether the market efficiently prices other information contained in analysts' forecast according to its association with earnings.

To test whether stock prices fully reflect the impact of other information contained in analysts' forecast on earnings, a specification of a "naive" expectation model is necessary, against which to test the null hypothesis of market efficiency. A parsimonious naive model applied to this situation is that the market prices the persistence of earning components and the impact of other information on earnings, but fails to price the appropriate impact of good and bad news on earnings. As measure of other information, we use the proxy suggested by Brian and Tiras (2007).

Following Sloan (1996) and Xie (2001), we use the Mishkin test (1983) and the hedge-portfolio test to investigate this issue. The framework of the Mishkin (1983) test starts from the basic implication that, conditional on a set of information, in expectation, abnormal returns are zero under market efficiency. If the market correctly anticipates the impact of other information contained in analysts' forecast of one-year-ahead earnings, then the market's valuation coefficient of other information should be statistically equal to the coefficient that relates this information with one-year-ahead earnings. On the other hand, if the coefficient relating current information to future earnings is not proportional to the coefficient relating that information to returns, then the null will be rejected. Since the forecasting coefficient is a measure of the average impact of other information on earnings, we attribute any mispricing of other information contained in analysts' forecast to the market's failure to correctly weigh this information according to its impact on earnings[9].

Several studies have documented a stronger reaction to bad news over good news by the market (DeBondt and Thaler (1985, 1987), Ou-Penman (1989), among others). At this point, evidences of this market behavior does not necessarily suggest irrationality. For example, in November 12, 1996, The Wall Street Journal speculates:

> "Analysts say that stocks that surprise analysts with better-than expected earnings are often rewarded with a ho-hum increase if any. However, the market is punishing stocks even more than usual for earnings disappointments... . Part of the problem is fear of the valuation levels that many stocks have reached. With the market at these levels, if stocks are slightly down (in terms of unexpected earnings), they get severely punished." (Deborah Lohse, The Wall Street Journal, p. C1, 1996.)

Regime-switching models, such as those introduced by David (1997) and Veronesi (1999), present explanations for this asymmetric market reaction based on the uncertainty about the overall state of the market. On the one hand, during a long period of good market performance, investors tend to become highly confident, which makes good news to have a lower marginal impact on investor beliefs and bad news to cause investors to infer lower probabilities that the market is performing in a good state, forcing investors to require higher expected rate of returns in order to hold the stocks. On the other hand, when investors expect that the overall economy is in a bad state and good news arrives, inferences that the market is performing in a good state tend to increase; "thus, the positive impact on prices is offset by the rising discount rate generated by increased investor uncertainty" (Conrad, Cornell, & Landsman, 2002). In both scenarios, the market seems forced to respond more strongly to bad news over good news.

Based on evidences that the market reacts strongly to bad news over good news[10], we expect a stronger market reaction to negative other information contained in analyst forecasts over positive other information contained in analyst forecasts. This prediction is also consistent with the assumption that stock market reacts for both positive and negative news, but that the market is generally stronger aversion to future losses than preferable for future gains[11]. Moreover, since other information and current stock returns

[9]At this point, several researchers have been concerned about the influence of analyst forecast bias on conclusions concerning market reaction. We argue, however, that under market efficiency, the market should be able to discern between the impact of other information on earnings and analyst bias. For example, if a public other information have an impact of $\$80$ millions on earnings and analysts forecast this impact as $\$100$ millions, then the market should be able to capture analysts' optimism and make the valuation process based on $\$80$ millions. In this case, the market should price the impact of information contained in analysts' forecast on earnings as 0.8, which represents the relation of analysts' expectation of that information with realized earnings.

[10]Basu (1997) associate good and bad news with positive and negative (unexpected) annual stock returns, under the assumption that the market rationally adjusts for the effects of conservatism on the reported accounting earnings. In our analysis, however, we associate good (bad) news with analysts' expected positive (negative) other information. Since change in expectations of future earnings and current stock returns have a positive association, our definition of good and bad news is consistent and appropriate for our purpose.

[11]The asymmetric relation between negative and positive current other information to current returns is consistent with the loss-aversion principle, as posited by Kahneman and Tversky (1979). In our context, the loss-aversion principle can be interpreted as the difference between the market's stronger aversion to an expected future earnings' decrease (negative other information) compared to the market's propensity to assess stocks related to an expected future earnings' increase (positive other information) of equivalent magnitude.

theoretically have a positive association, firms with negative (positive) other information should experience negative (positive) returns.

Empirical analyses confirm our predictions. As expected, other information are positively correlated with current returns and size-adjusted abnormal returns, and also with earnings, but are not correlated with past earnings. The results of the Mishkin test suggest that the market acts as if it on average underprices the impact of good news and overprices the impact of bad news on earnings, which is consistent with our assumption that the market gives on average more weight for bad news than for good news. A non linear analysis suggests, however, that the market tends also to overprice the impact of positive other information when the expected impact of this information on earnings is sufficiently large.

Based on these results, if a trading strategy taking a long position in firms with past extreme negative other information and a short position in firms with past extreme positive other information yields positive abnormal stock returns, then the hedge-portfolio test would corroborate with evidences that the market overprices extreme other information contained in analysts' forecast in the portfolio formation year.

Decile portfolios were formed annually by ranking firms according to other information. Our results suggest that the market's overpricing of bad news increase with the magnitude of the expected impact of this information on earnings. Consistent with our prior results, the lowest (highest) decile portfolios based on other information experience positive (negative) size-adjusted abnormal returns in the year after the portfolio formation. At this point, the hedge portfolio generates positive and significant returns and support the overpricing of extreme other information, as suggested by our non-linear Mishkin test. These result are consistent with evidences presented by So (2013) that investors overweight information contained in analyst forecasts.

To confirm that the hedge portfolio test's results lead overpricing conclusions, we also estimate a two-years-ahead earnings model. If in controlling for past earnings components we find a positive incremental effect of other information on two-years-ahead earnings, then it would corroborate with an overpricing of other information in the portfolio formation year. This implication follows once if good (bad) news that impact next year earnings are persistent and also have a positive (negative) incremental effect on two-years-ahead earnings, then portfolios based on past other information should also experience non-negative (non-positive) abnormal returns in the following year, conditional on the market correctly pricing other information in the portfolio formation year. The results of this two-years-ahead model also corroborates with overpricing conclusions.

We also predict that, when analysts focus on news and there is an analysts consensus about the impact of such news on earnings, the market is more likely to misprice the impact of other information contained in analysts' forecast. We expect that because if analysts highlight a news and have common expectations about the impact of this news on earnings, then the market is more likely to follow analysts. If we find evidences that the market act as if it does not understand (overprices) the impact on earnings of good and bad news contained in analysts' forecast, then firms-year subject to extreme news should be more likely to experience higher abnormal returns when analysts agree about the expected impact of such information. Therefore, the hedge portfolio test should provide higher abnormal returns for firms-year in such cases. In general, our results confirm this prediction by suggesting that the market misprices other information leading to arbitrage, which is larger when the expected impact of this information on earnings is sufficiently large and analysts agree about it.

By identifying the role of other information contained in analysts' forecast in the market assessment of future earnings, our study provides a setting that corroborate and extend prior literature. In summary, we extend the current literature by presenting evidences that the market does not correctly price the impact of information other than earnings, book value, and dividends contained in analysts' forecast, and also fails to linearly price the impact of good and bad news on earnings. Moreover, we provide evidences that the market misprices other information leading to arbitrage, which is larger when the expected impact of this information on earnings is sufficiently large and analysts agree about it.

The remaining of the article is organized as follows. In the next section we provide a theoretical analysis of the relations among one-year-ahead earnings news, the impact of this information on earnings, and a hypothetical other information market weight function, in order to support our hypotheses. In section 3, we describe the sample selection procedure and the empirical data. Section 4 provides our results. Finally, in section 5 we provide a summary and conclusions.

2.2 A THEORETICAL ANALYSIS

This section provides a theoretical analysis of the relation among one-year-ahead earnings news, a hypothetical other information market weight function, the market' expectation of the impact of other information on earnings, and the impact of this information as reflected in its association with one-year-ahead earnings. In particular, we claim that: $A)$ the market reacts for both negative and positive other information; $B)$ the market gives more weight for bad news (other information that have an expected negative impact on future earnings) than for good news (other information that have an expected positive impact on future earnings), which is consistent with the loss-aversion principle, as showed by Kahneman and Tversky (1979); and that $C)$ these weights increase marginally with the magnitude of good and bad news.

2.2.1 A Hypothetical Market Weight Function

In order to point a link between any market anomaly according to other information and the market's failure to correctly weighs other information according to its association with realized earnings, let us consider the continuous function $V : W \subset R^n \to R$ based on the market internal mechanism, which value the other information available in the environment W according to its expected impact on one-year-ahead earnings. Denote $w_t = (v_t^1, v_t^2, \ldots, v_t^n) \in W$ as the set of other information available at period t, v_i as the expected impact on next year earnings of the information v_t^i, and v_i^* as the respective true impact on one-year-ahead earnings of the information v_t^i, $i = 1, 2, \ldots, n$. If the market known at time t the true impact v_i^* of each information v_t^i on future earnings, then the expected aggregate impact V_t on one-year-ahead earnings due to the set of other information w_t would be

$$V_t = V_t^* = \sum_{i=1}^{n} v_i^* \tag{1}$$

where V_t^* is the true aggregate impact on one-year-ahead earnings due to the set of other information w_t. But as v_i^* is not always known, and individuals form different expectations about the impact of each information v_t^i on future earnings, we can not assume that the expected total impact of other information on future earnings is given as in equation 1.

Without loss of generality, let us assume that corr$(v_t^i, v_t^j) = 0$, for all $i \neq j$. By this way, a natural and parsimonious form for the function V can be given by

$$V_t = V(v_t^1, v_t^2, \ldots, v_t^n) = \sum_{i=1}^{n} E_t[v_i^*] = \lambda_1 v_1^* + \lambda_2 v_2^* + \ldots + \lambda_n v_n^* = \; < \Lambda, z_t^* > \tag{2}$$

where $z_t^* = (v_1^*, v_2^*, \ldots, v_n^*)$, $\lambda_i = \lambda_i(v_t^i) = \frac{\partial V}{\partial v_t^i}$ is a specific market function associated to the other information v_t^i, $i = 1, 2, \ldots, n$, which weigh on average each information v_t^i according to its expected impact on one-year-ahead earnings, and such that $\lambda_i v_i^* = v_i$. In other words, V can be written[12] as the internal product between the weight vector $\Lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n)$ and the vector $z_t^* = (v_1^*, v_2^*, \ldots, v_n^*)$ of the true impacts of the available other information.

In general, if the market was able to correctly value the impact of each other information v_t^i on one-year-ahead earnings, then $\lambda_1(v_t^1) = \lambda_2(v_t^2) = \ldots = \lambda_n(v_t^n) = 1$, and $V_t = V_t^* = \sum_{i=1}^{n} v_i^*$, as in equation 1. However, if the market does not correctly value the impact on one-year-ahead earnings for at least one other information, then $V_t > V_t^*$ or $V_t < V_t^*$. In other words, $V_t = V_t^* + \epsilon$, $\epsilon \neq 0$. Using the definitions above, we can rewrite this statement as

$$V_t = \Lambda . z_t^* = \overrightarrow{u} . v_t^* + \overrightarrow{r} . v_t^* \quad \Rightarrow \quad \overrightarrow{r} = \Lambda - \overrightarrow{u}$$

where $\overrightarrow{u} = (1, 1 \ldots, 1)$, $\overrightarrow{r}$ is a non-null market weight error vector, and $\epsilon = \overrightarrow{r} . v_t^*$. In other words, it would mean that any mispricing of other information comes from the market's failure to correctly weighs at least one other information according to its association with future earnings.

To show how this hypothetical function is related with $B)$ and $C)$, let us consider, for simplicity, the set of other information $w_t = (v_t^1, -v_t^1)$ associated to a specific firm, such that $v_1^* > 0$. It means that there are two contrary and unrelated events that should impact this firm's one-year-ahead earnings in equal magnitude. If the market was able to correctly value the impacts of this information on one-year-ahead earnings, then $\lambda_1(v_t^1) = \lambda_2(-v_t^1) = 1$ and $V_t = 0$. However, if the market does not correctly value the impacts of this information, then $V_t = \lambda_1 . v_1^* - \lambda_2 . v_1^*$ could be positive or negative, and therefore, $\lambda_1(v_t^1) > \lambda_2(-v_t^1)$ or $\lambda_1(v_t^1) < \lambda_2(-v_t^1)$, respectively. In other words, it would mean that any mispricing of other information would comes from the market's failure to correctly weighs other information according to its association with future earnings. As several studies have documented a market stronger reaction to bad news over good news (DeBondt and Thaler (1985, 1987), Ou-Penman (1989), among others), we expect that on average the market gives more weight for bad news than for good news ($\lambda_1(v_t^1) < \lambda_2(-v_t^1)$), and that these weights increase marginally with the magnitude of v_t^1. These predictions allow us to state the next hypotheses:

However, in the actual empirical setting we are still not able to measure the expected impact of each other information v_t^i on one-year-ahead earnings. The methodologies present in the current literature allow

[12]We are assuming that the market distinguishes between information v_t^i and v_t^j, and its respective weights $\lambda_i(v_t^i)$ and $\lambda_j(v_t^j)$, but that the relation between an other information v_t^i and the respective expected value of the impact of this information on future earnings have been driven by a market internal mechanism, which is reflected in the outcome $v_i = \lambda_i v_i^*$.

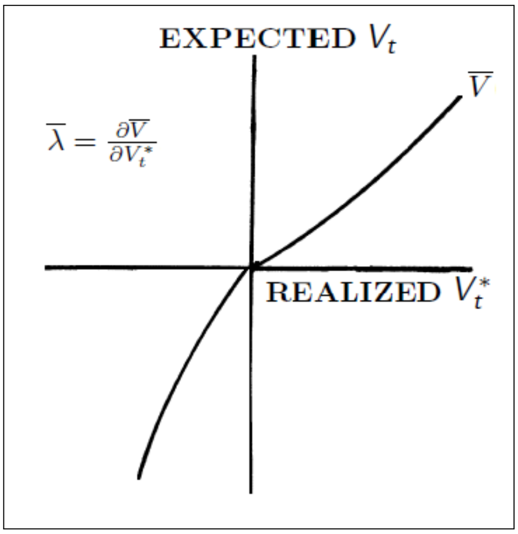


Figure 1: A hypothetical market function that associate the realized impact with the expected impact of other information on one-year-ahead earnings.

us only to proxy for the expected aggregate impact V_t of other information. In spite of this fact, we can consider an average market weight function $\overline{\lambda} = \frac{\partial \overline{V}}{\partial V_t^*}$, in which

$$\overline{V}(V_t^*) = V_t = V(v_t^1, v_t^2, \ldots, v_t^n) \tag{3}$$

In this case, $\overline{\lambda} = 1$ would indicate that the market on average correctly weighs other information according to its impact on one-year-ahead earnings, and $\overline{\lambda} > 1$ ($\overline{\lambda} < 1$) indicates that the market on average overweighs (underweighs) other information according to its association with one-year-ahead earnings.

According to the definitions and relations presented above, a function $\overline{V}$ that satisfies these relations and our claims $B)$ and $C)$, must also satisfy, for all $V_t^* > 0$:

(a) $\overline{V}(V_t^*) < \overline{V}(-V_t^*)$

(b) $\overline{V}'(V_t^*) < \overline{V}'(-V_t^*)$

(c) $\overline{V}''(-V_t^*) < 0 < \overline{V}''(V_t^*)$

These conditions lead the graph for the average market function $\overline{V}$, as shown in Figure 1. Note that this hypothetical market function is generally convex for gains and concave for losses, and steeper for losses than for gains. Intuitionally, $a)$, $b)$, and $c)$ suggest respectively that the market expects on average a larger impact on future earnings for bad news over good news of the same magnitude, the market gives a larger weight for bad news than for good news, and that these average weights marginally increase with the increasing of good and bad news. These characteristics are consistent with the idea that the market is stronger aversion to future losses than preferable for future gains (loss-aversion principle), and that the market usually requires a higher degree of verification to recognize future gains over future losses in a conservative accounting system.

2.2.2 The Market Assessment of Other Information

In this subsection we point the relation among the theoretical average market weight function $\overline{\lambda}$, the other information outcome V_t, and the market assessment of this average market weight function, using the framework of the Mishkin (1983) test and the information provided by analysts. The Mishkin test starts from the basic implication that, conditional on a set of information available to the market at the end of period t, in expectation, abnormal returns are zero under market efficiency. It means that

$$E[\text{RET}_{t+1} - \text{RET}^m_{t+1}|\phi] = 0 \tag{4}$$

where RET_{t+1} is the firm's annual buy-and-hold return for period $t+1$, and RET^m_{t+1} is the market's subjective expectation of the normal return for period $t+1$.

If X is a relevant variable to explain price, so a model that satisfies the efficient market condition, conditional on the set of information ϕ, is

$$(\text{RET}_{t+1} - \text{RET}^m_{t+1}|\phi) = \beta\left(X_{t+1} - E[X_{t+1}|\phi]\right) + e_t \tag{5}$$

where $E[X_{t+1}|\phi]$ is the rational forecast of X_{t+1} at time t, β is a valuation multiplier, and e_t is a disturbance with zero mean conditional to the set of information ϕ. In our context, the relevant variable X is one-year-ahead earnings EARN_{t+1}, stated as

$$\text{EARN}_{t+1} = \gamma_0 + \gamma_1\text{CFO}_t + \gamma_2\text{NAC}_t + \gamma_3\text{ABNAC}_t + \gamma_4\widehat{V}_t + e_{t+1}$$

where

- CFO_t = cash flow from operating activities;
- NAC_t = normal accruals, given by the predicted value of the Jones (1991) model, estimated in time series per firm;
- ABNAC_t = abnormal accruals, given by the residual of the Jones (1991) model;
- $\widehat{V}_t$ = other information, estimated as the residuals of the time series regression of next year's earnings consensus analysts' forecast on past earnings, book value, and dividends;
- γ_i = average historical persistence of earnings components $(i = 1, 2, 3)$ and other information $(i = 4)$, respectively, as reflected in its association with one-year-ahead earnings;

Based on this framework, the regression system to be estimated is composed by the following equations[13]:

$$\text{EARN}_{t+1} = \gamma_0 + \gamma_1\text{CFO}_t + \gamma_2\text{NAC}_t + \gamma_3\text{ABNAC}_t + \gamma_4\widehat{V}_t + e_{t+1} \tag{6}$$

$$\text{ABRET}_{t+1} = \alpha + \beta\left(\text{EARN}_{t+1} - \gamma^*_0 - \gamma^*_1\text{CFO}_t - \gamma^*_2\text{NAC}_t - \gamma^*_3\text{ABNAC}_t - \gamma^*_4\widehat{V}_t\right) + \epsilon_{t+1} \tag{7}$$

[13]The equations 6 and 7 will be estimated jointly using a two stages iterative generalized non linear least square estimation procedure, as in Mishkin (1983).

where $\text{ABRET}_{t+1} = \text{RET}_{t+1} - \text{RET}^m_{t+1}$.

Mishkin (1983) shows that the forecasting coefficient γ_i and the valuation coefficient γ_i^* can be statistically compared by the likelihood ratio $\mathcal{X}^2(i) = 2N \ln\left(\text{SSR}^c/\text{SSR}^u\right)$, which is asymptotically $\mathcal{X}^2$ distributed. N represents the number of sample observations, and SSR^u and SSR^c represent the sum of squared residuals from the estimated regression system formed by equations 6 and 7, imposing any constraint, and imposing the rational pricing constraint $\gamma_i = \gamma_i^*$, respectively.

In this case, if the market correctly anticipates the impact of other information contained in analysts' forecast, then the valuation coefficient γ_4^* of other information should be statistically equal to the forecasting coefficient γ_4. In other words, under market efficiency, the market's assessment of the impact of other information contained in analysts' forecast should be statistically equal to the impact of this information on future earnings. On the other hand, if the coefficient relating current information to future earnings is not proportional to the coefficient relating that information to returns, then the null will be rejected. In this case, the Mishkin test would indicate that the market misprices other information contained in analysts' forecast[14].

At this point, our hypothetical market weight function $\overline{\lambda}$ can be obtained from the coefficients given by the Mishkin test:

$$1 + \frac{\gamma_4^* - \gamma_4}{\lambda_4} \cong \overline{\lambda} \tag{8}$$

In this case, test the null $\gamma_4 = \gamma_4^*$ is equivalent to test the null $\overline{\lambda} = 1$. If we do not reject the null, then it would indicate that the market on average correctly weighs other information contained in analysts' forecast according to its association with future earnings. But if we can not reject that $\overline{\lambda} > 1$ ($\overline{\lambda} < 1$), then it would suggest that the market on average overweighs (underweighs) the impact of such information on one-year-ahead earnings. This framework allow us to state our first set of hypotheses:

H1(i): *The market prices the impact of other information contained in analysts' forecast according to its association with one-year-ahead earnings, but fails to price appropriately the impact of such information* ($\overline{\lambda} \neq 1$).

H1(ii): *The market reacts more strongly to negative other information contained in analyst forecast than to positive other information contained in analyst forecast* ($\overline{\lambda}_- > \overline{\lambda}_+$).

2.2.3 The Equivalence between the Mishkin Test and OLS

In the usual accounting settings, the Mishkin test is applied to test whether the persistence of accounting components are rationally priced according to its association with the rational forecast of a specific variable. However, it is not easy to address in these analyses some important econometric issues or to include additional and relevant explanatory variables, since the statistic used to compare the estimated coefficients

[14]At this point, several researchers have been concerned about the influence of analyst forecast bias on conclusions concerning market reaction. We argue, however, that under market efficiency, the market should be able to discern between the impact of other information on earnings and analyst bias. For example, if a public other information have an impact of $\$80$ millions on earnings, and analysts forecast this impact as $\$100$ millions, then the market should be able to capture analysts' optimism and make the valuation process based on $\$80$ millions. In this case, the market should price the impact of information contained in analysts' forecast on earnings as $\lambda^* = 0.8$, which represents the relation of analysts' expectation of that information with future earnings ($\lambda = 0.8$).

is $\mathcal{X}^2$ distributed and depends of particular convergency criteria. As briefly demonstrated by Kraft et al (2007), the equivalence between the Mishkin test and a OLS model in large samples allow us to implement these issues[15].

Replacing the forecasting equation 6 into the return equation 7, we get the following OLS model [16]:

$$\text{ABRET}_{t+1} = \alpha + \beta(\gamma_0 - \gamma_0^*) + \phi_1 \text{CFO}_t + \phi_2 \text{NAC}_t + \phi_3 \text{ABNAC}_t + \phi_4 \widehat{V}_t + \epsilon_{t+1} \tag{9}$$

where $\phi_i = \beta(\gamma_i - \gamma_i^*)$, with $i = 1, 2, 3$ or 4. As β is a non null constant, test the null hypothesis $H_0 : \phi_i = 0$ is equivalent to test the market efficiency hypothesis $H_0 : \gamma_4^* = \gamma_4$. In our setting, a ϕ_4 statistically equal to zero indicates that the market correctly prices the persistence of other information according to its association with one-year-ahead earnings. But if ϕ_4 is statistically negative (positive), then the t-test would indicate that the market overprices (underprices) the impact of other information on future earnings[17]. In this case, our measure of the average market weight function $\overline{\lambda}$ can be rewritten as

$$1 - \frac{\phi_4}{\beta\gamma_4} \cong \overline{\lambda} \tag{10}$$

Since the coefficient β and the forecasting coefficient γ_4 are positive, the interpretation of $\overline{\lambda}$ follows analogous to it prior interpretation, except that now it depends on the signal and the significance of ϕ_4, instead of the distance between the valuation coefficient γ_4^* and the forecasting coefficient γ_4.

2.2.4 A Non-Linear LS Model

In order to make empirical inferences about the marginal variation of the impact of information contained in analysts' forecast on stock returns, we consider the following quadratic model[18]:

$$\text{ABRET}_{t+1} = \phi_0 + \sum_{i=1}^{4} [\phi_{1i} X_i + \phi_{2i} D_i X_i + \phi_{3i} X_i^2 + \phi_{4i} D_i X_i^2] + \epsilon_{t+1} \tag{11}$$

where X_1, X_2, X_3, and X_4 represent $\text{CFO}_t, \text{NAC}_t, \text{ABNAC}_t,$ and $\widehat{V}_t$, respectively. D_i is a dummy set as 1 if X_i is negative, and 0, otherwise. In this model, if ϕ_{2i} is significant, it would suggest that the market prices

[15]Mishkin (1983) and Abel and Mishkin (1983a) demonstrate that the estimated parameters and statistics of test of the Mishkin test and an equivalent OLS model are asymptotically the same. Abel and Mishkin (1983a) show that this equivalence hold not only asymptotically, but also for finite samples, after some adjustments for degrees of freedom.

[16]Note that in equation 9 the term βe_{t+1} was omitted. Since β is a constant and by construction e_{t+1} was designed to be orthogonal to earnings components and other information, this exclusion does not cause asymptotically any bias in the estimation of the coefficients of these variables.

[17]Although the OLS is an easier method to implement and allows more straightforward comparisons among accounting researches, this method has a disadvantage according to its interpretation. On one hand, if β is not significant, we cannot make any inference about the relation between abnormal returns and the residuals of the forecasting equation. On the other hand, if β is negative, then a negative (positive) coefficient ϕ would indicate that the market underprices (overprices) the persistence of the respective variable, instead of overprices (underprices). If accounting researchers decide to use the OLS method, we suggest them to state more explicitly the theoretical reasons that support the signal and the significance of the coefficient β in their research settings or, alternatively, consider using both methods or only the Mishkin test.

[18]We are also including in our model dummies for negative earnings components and quadratic terms for these components in order to verify if the misprice of normal and abnormal accruals documented by Xie (2001) increase or decrease with the magnitude of these components, and if the underpricing of cash flows documented by Sloan (1996) holds for firms-year with cash flows sufficiently high.

the persistence of the negative values of X_i differently from the positive values of X_i. If ϕ_{3i} is significant, it would suggest that on average the market prices the persistence of the variable X_i according to the magnitude of X_i. And if ϕ_{4i} is significant, then it would suggest that on average the market marginally prices the persistence of the negative values of the variable X_i differently from the positive values of this variable.

Based on the non-linear model 11, our hypothetical average market function $\overline{V}$ and our average market weight function $\overline{\lambda}$ could be written respectively as

$$\overline{V}(V_t^*) = \begin{cases} \overline{\lambda}_1 V_t^* + \overline{\lambda}_3 V_t^{*2}, & \text{if } V_t^* \geq 0 \\ \overline{\lambda}_2 V_t^* + \overline{\lambda}_4 V_t^{*2}, & \text{if } V_t^* < 0 \end{cases} \tag{12}$$

and

$$\overline{\lambda}(V_t^*) = \frac{\partial \overline{V}(V_t^*)}{\partial V_t^*} = \begin{cases} \overline{\lambda}_1 + 2\overline{\lambda}_3 V_t^* & \text{if } V_t^* \geq 0 \\ \overline{\lambda}_2 + 2\overline{\lambda}_4 V_t^* & \text{if } V_t^* < 0 \end{cases} \tag{13}$$

Once we estimate the coefficients $\phi_{41}, \phi_{42}, \phi_{43}$, and ϕ_{44} of the non-linear model 11, we will be able to make empirical inferences about the signals of the coefficients $\overline{\lambda}_1, \overline{\lambda}_2, \overline{\lambda}_3$, and $\overline{\lambda}_4$ of the market function $\overline{V}$ presented above, since the market weight function $\overline{\lambda}$ and our LS coefficients are connected. By this way, we will be able to empirically verify if the weights given by the market to good and bad news marginally increase with the magnitude of these news. This theoretical framework allow us to state our next hypothesis:

H1(iii): *The mispricing of other information contained in analyst forecasts increases marginally with the magnitude of good and bad news* ($\overline{\lambda}_3 > 0 \;\; (\phi_{43} < 0)$ *and* $\overline{\lambda}_4 < 0 \;\; (\phi_{44} > 0)$).

2.2.5 Further Hypotheses

Theoretically, firms with negative other information should experience on average negative returns and firms with positive other information should experience on average positive returns, conditional on the set of other information. If a trading strategy taking a long position in firms with past negative other information and a short position in firms with past positive other information yields positive abnormal stock returns, then the hedge-portfolio test would provide evidences that the market overprices other information in the portfolio formation year. This implication allow us to state our next hypothesis.

H2: *A trading strategy taking long position in firms with negative other information and a short position in firms with positive other information generates positive abnormal stock returns in the subsequent year.*

When analysts focus on news and there is an analysts consensus about the impact of such news on future earnings, the market is more likely to misprice the impact of other information on future earnings. We expect that because if analysts highlight a news and have common expectations about the impact of this news on future earnings, then the market is more likely to follow analysts. If we find evidences that the market act as if it does not understand (overprices) the impact on future earnings of good and bad news contained in analysts' forecast, then firms-year subject to extreme news should be more likely to experience higher abnormal returns when analysts agree about the expected impact of such information on future earnings. Therefore, the hedge portfolio test should provide higher abnormal returns for firms-year in such case. This prediction formally allows us to state our last hypothesis:

> **H3**: *The abnormal return obtained in the hedge portfolio test is larger when analysts agree about the expected impact of extreme news on future earnings.*

If empirical analyses confirm our hypotheses, our results would suggest that the market does not correctly price the impact of other information contained in analysts' forecast according to its association with one-year-ahead earnings, and also fails to price appropriately the impact of bad and/or good news on future earnings. Moreover, our results would also provide evidences that the market misprices other information leading to arbitrage, which could be larger when analysts agree about the expected impact of this information on future earnings.

2.3 SAMPLE SELECTION PROCEDURE AND THE EMPIRICAL DATA

Our initial sample was identified by merging Compustat-listed firms with firms listed on I/B/E/S from 1983 to 2012. Monthly returns data were obtained on CRSP database. Firms from regulated financial institutions and utilities (SIC codes between 6000 and 6999), and firms-year with negative book value were excluded. Observations with missing Compustat data or with missing I/B/E/S data of analysts' forecast were also deleted. We also restricted I/B/E/S data for firms-year followed by at least two analysts. Finally, we considered firms that have all the required data available for at least 10 years during the sample period in order to estimate our proxy of other information. In the end, we obtained a sample size of $41,243$ firms-year over our 30-years sample period. All the variables were winsorized yearly at 1% and 99% level to mitigate possible influences of outliers.

In our analysis, earnings EARN_t are defined as income before extraordinary items (Compustat item $\#18$), book value BV_t is set as total common equity (Compustat item $\#60$), and DIV_t represents total dividends paid at the end of each fiscal year (sum of Compustat items $\#19$ and $\#21$, plus dividends other than stock dividends declared on other share capital of the company and based on the current year's net income). As proxy for the expected value of one-year-ahead earnings, we use consensus analysts' forecast (CAF_t), given by the median[19] of the analysts' forecast of the next year's earnings made in the period between the fiscal-year-end and the earnings announcement. As in Brian and Tiras (2007), we estimate our proxy $\widehat{V_t}$ of other information for each firm as the residual of the time series regression[20] of next year earnings consensus analysts' forecast on past earnings, book value, and dividends:

$$\widehat{V_t} = \text{CAF}_t - \widehat{\delta_1}\text{EARN}_t - \widehat{\delta_2}\text{BV}_t - \widehat{\delta_3}\text{DIV}_t \tag{14}$$

Following Sloan (1996), we estimate size-adjusted abnormal return ABRET_t as the difference between the firm's buy-and-hold return RET_t for the 12-month period ending three months after the fiscal-year-end, and the market's subjective expectation of the normal return RET_t^m set as the buy-and-hold

[19] We also use the mean of one-year-ahead earnings analysts forecast as proxy for the expected value of the next year earnings. All our conclusions follow as the same.

[20] We estimate our proxy of other information firm-by-firm in a time series regression, once the impact of non-accounting information on next year earnings must be affected by particular conditions like firm's economic pressure, production technology, and others firm's specific characteristics. Adding conditioning variables to control for these forces is difficult (Myers 1999).

return for the same 12-month period of the market-capitalization-based portfolio decile in which the firm belongs. Total accruals TAC_t are measured by the difference between earnings EARN_t and cash flow from operating activities CFO_t, reported under SFAS no.95 (Compustat item $\#308$), i.e.,

$$\text{TAC}_t = \text{EARN}_t - \text{CFO}_t$$

For the period before 1988 when Compustat item $\#308$ is not available, we estimate cash flow as the sum of funds from operations FFO_t (Compustat item $\#110$), change in cash and short term investment ΔCASH_t (Compustat item $\#1$), and change in current liabilities ΔCL_t (Compustat item $\#5$), minus the change in short term debt ΔSTD_t (Compustat item $\#34$), and minus the change in current assets ΔCA_t (Compustat item $\#4$), as follows:

$$\text{CFO}_t = \text{FFO}_t + \Delta\text{CASH}_t + \Delta\text{CL}_t - \Delta\text{STD}_t - \Delta\text{CA}_t$$

As in Xie (2001), we consider normal accruals NAC_t as the predicted value of Jones (1991) model, estimated in time series for each firm:

$$\text{NAC}_t = \widehat{\text{TAC}}_t = \widehat{\alpha_0} + \widehat{\alpha_1}\Delta\text{REV}_t + \widehat{\alpha_2}\text{PPE}_t \tag{15}$$

where ΔREV_t represents changes in sales revenue in fiscal year t (Compustat item $\#12$), and PPE_t is gross property, plant, and equipment (Compustat item $\#7$). All variables were deflated by the beginning-of-fiscal-year total assets TA_{t-1} (Compustat item $\#6$). Abnormal accruals ABNAC_t are given by the residuals of the Jones (1991) model, i.e.,

$$\text{ABNAC}_t = \text{TAC}_t - \text{NAC}_t$$

Panel A of Table 1 presents descriptive statistics for the sample. The results for earnings components, returns, and size-adjusted abnormal returns are comparable to those reported on Xie (2001, Table 1, Panel A), regardless of differences in the sample period. Untabulated results review that the mean of abnormal accruals and other information are not different than zero at 1% significance level, and that the mean of analysts' forecast is lower than the mean of one-year-ahead earnings. The frequency of positive consensus analysts' forecast, however, is higher than the frequency of positive one-year-ahead earnings. This difference in frequency is consistent with evidences present in the literature which suggest that analysts are generally optimistic (Das, Levine and Sivaramakrishnan, 1998; Lim, 2001; and Cowen, Groysberg and Healy, 2006). Other information contained in analysts' forecast have almost the same frequency between negative and positive values (47.62% of $\widehat{V}_t$ are positive).

An untabulated t-test reviews that the absolute value of the mean of negative other information is statistically higher than the mean of positive other information at 1% significance level. The same result holds when we consider intervals centralized on zero and containing $5\%, 10\%, 15\%, 20\%$, and 25% of negative and positive ranked other information, respectively. Untabulated results for Skewness/Kurtosis tests also review that other information are normally distributed at 1% significance level.

Panel B of Table 1 provides Pearson and Spearman correlations between the selected variables. As we expected, returns and size-adjusted abnormal returns are positively correlated with next year earnings, and earnings components are positively correlated with past and future earnings. Untabulated results review that returns and size-adjusted abnormal returns are also positively correlated with analysts' forecast,

Table 1: **Descriptive Statistics and Correlations**

Panel A: Descriptive Statistics[a]

Variables[b]	Mean[c]	Std. Dev.	Median	Min.	Q1	Q3	Max.	% Positive
RET_{t+1}	0.202	0.781	0.105	-0.973	-0.131	0.370	53.663	61.63
ABRET_{t+1}	0.072	0.726	-0.015	-1.729	-0.222	0.216	52.166	48.06
CAF_t	0.040	0.142	0.039	-2.923	0.016	0.076	1.06	89.44
EARN_{t+1}	0.051	0.123	0.057	-1.851	0.023	0.102	0.436	83.92
EARN_t	0.051	0.149	0.058	-2.608	0.024	0.105	0.477	84.39
CFO_t	0.103	0.162	0.107	-3.457	0.059	0.165	0.605	89.42
NAC_t	-0.058	0.099	-0.052	-3.574	-0.084	-0.027	0.779	12.38
ABNAC_t	0.001	0.090	0.002	-3.289	-0.027	0.032	1.417	52.21
$\widehat{V}_t$	0.000	0.079	-0.001	-2.189	-0.017	0.015	1.152	47.62

Panel B: Pearson (below diagonal) and Spearman (above diagonal) Correlations

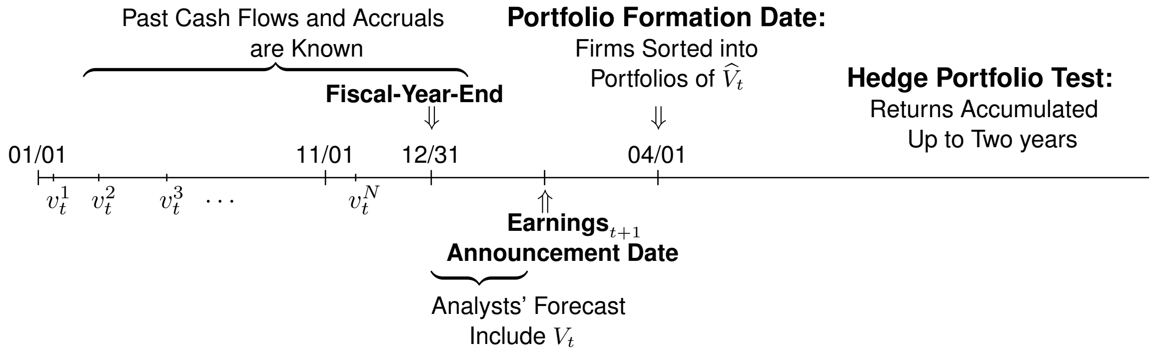
	RET_{t+1}	ABRET_{t+1}	EARN_{t+1}	EARN_t	CFO_t	NAC_t	ABNAC_t	$\widehat{V}_t$
RET_{t+1}		0.827***	0.191***	-0.004	0.038***	-0.004	-0.056***	0.030***
ABRET_{t+1}	0.955***		0.207***	0.003	0.043***	-0.004	-0.051***	0.055***
EARN_{t+1}	0.082***	0.082***		0.699***	0.525***	0.148***	-0.025***	0.278***
EARN_t	-0.052***	-0.050***	0.68***		0.612***	0.206***	0.131***	-0.007
CFO_t	-0.018***	-0.016***	0.565***	0.710***		-0.274***	-0.347***	0.053***
NAC_t	-0.020***	-0.025***	0.280***	0.445***	0.032***		-0.101***	-0.005
ABNAC_t	-0.030***	-0.026***	0.021***	0.276***	-0.173***	-0.006		-0.096***
$\widehat{V}_t$	0.017***	0.026***	0.287***	0.002	0.046***	0.013***	-0.103***	

[a] Our sample is identified by merging firms listed on Compustat and I/B/E/S from 1983 to 2012. The monthly returns data were obtained on CRSP database. In the end, we obtained a sample size of $41,243$ firms-year observations over our 30-year sample period.

[b] Variables definitions:

- RET_{t+1} = firm's buy-and-hold return for the 12-month period ending three months after the fiscal-year-end;
- ABRET_{t+1} = size-adjusted abnormal return, estimated as the difference between the firm's buy-and-hold return and the buy-and-hold return for the same 12-month period on the market portfolio decile in which the firm belongs;
- CAF_t = consensus analysts' forecast, estimated as the median of analysts' forecast;
- EARN_t = income before extraordinary items;
- CFO_t = cash flow from operating activities;
- NAC_t = normal accruals, given by the predicted value of Jones (1991) model, estimated by firm in a time series regression;
- ABNAC_t = abnormal accruals, given by the residual of the Jones (1991) model;
- $\widehat{V}_t$ = other information, estimated as the residuals of the time series regression of consensus analysts' forecast on past earnings, book value, and dividends;

[c] $*$, $**$, and $***$ represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.



and analysts' forecast are positively correlated with other information and next year's earnings. As we also expected, other information are not correlated with past earnings, and are positively correlated with returns, size-adjusted returns, and next year earnings.

2.4 EMPIRICAL RESULTS

This section provides our results. We proceed with the estimations as follow: first, we apply the Mishkin test for the entire sample over our 30-year sample period. After that we create for each year two other-information portfolios (a positive and a negative portfolio) based on the ranked values of $\widehat{V}_t$. The positive (negative) portfolio is formed by firms-year that have their respective other information in the positive (negative) domain of other information. The assessment of the Mishkin test coefficients for the entire sample and for both portfolios during the entire period allow us to test our hypotheses $H1(i)$ and $H1(ii)$, respectively. In order to test the hypothesis $H1(iii)$, we estimate the non-linear model 11.

We also group firms annually based on the ranked values of other information in order to build our hedge portfolio. Time-series means of size-adjusted abnormal returns are calculated for each other-information decile portfolio up to two years after the portfolio formation. The hedge portfolio is formed by taking a long position in the lowest other-information decile portfolio, and a short position in firms-year which belong to the highest other-information decile portfolio. This procedure allow us to access our hypothesis $H2$.

Finally, in order to assess our hypothesis $H3$, we rank firms yearly according to the standard deviation of analyst forecasts (scaled by the respective mean of analyst forecasts). After that we split each analyst-forecast-dispersion portfolio based on the decile of other information, in order to generate portfolios with low/high analyst forecast dispersion, and positive/negative other information. As in Brian and Tiras (2007), the high analyst-forecast-dispersion portfolio is formed by all firms which belong to the top 30% analyst forecast standard deviation centile, and the low analyst-forecast-dispersion portfolio is formed by all firms which belong to the bottom 30% analyst forecast standard deviation centile. At this point, we consider only firms which belong to the extreme deciles of other information to apply the hedge portfolio test. The assessment of the hedge portfolio test's results for both portfolios during the entire period allow us to test our hypothesis $H3$.

The time line presented in the above diagram uses a firm-year with December 31st fiscal-year-end as an illustration of our research design. This time line is used to emphasize that we avoid look ahead biases when forming investment portfolios and implementing the hedge portfolio test[21]. Enforcing a minimum of three-month separation between the fiscal-year-end and the portfolio formation date figures as a conservative procedure that mitigates the influence of any earnings surprise on future returns, and to assure that earnings of all December 31st fiscal-year-end firms-year were announced.

In terms of investment portfolio formation, however, the procedures used to estimate normal accruals, abnormal accruals, and other information generate an "investment look ahead bias". For example, in terms of other information, this investment look ahead bias is generated because estimate other information per firm as the residual of the regression of consensus analysts' forecast on past earnings, book value, and dividends using all firm observations would require that analysts known at the first years firm's information about future years (the same investment look ahead bias exists in estimating abnormal accruals using time series regressions). An alternative procedure that avoid this problem is estimate other information and abnormal accruals in time series regressions per firm, but considering for each year time series regressions based on observations of past years[22].

2.4.1 The Mispricing of Other Information

Panel A, B, and C of Table 2 present the forecasting and valuation coefficients of equations 5 and 6 obtained in the first stage for our entire sample, and for the positive and negative other-information portfolios. In order to verify if the forecasting coefficient γ_i and the valuation coefficient γ_i^* are proportional, we jointly estimate for each i the forecasting and return equations in a second stage, imposing the rational pricing constraint $\gamma_i = \gamma_i^*$. The significance of the likelihood ratio statistics obtained for each estimation are indicated in the last column of each Panel.

Panel A of Table 2 shows that the forecasting and valuation coefficients obtained for the earnings components are slightly lower than those reported on Xie (2001). The forecasting coefficients γ_1, γ_2, and γ_3 of cash flows, normal accruals, and abnormal accruals, equal 0.4323, 0.3224, and 0.2042, respectively. The respective valuation coefficients γ_1^*, γ_2^*, and γ_3^* equal 0.5224, 0.4931, and 0.4095. The significance of each likelihood ratio statistics indicated in the last column of this Panel suggests that the market on average overprices the persistence of normal and abnormal accruals at 1% significance level, which is consistent with the Mishkin test's results presented by Xie (2001). The relative distances between the forecasting and the valuation coefficients of normal and abnormal accruals equal $52,95\%$ and $100,54\%$, respectively,

[21] Although in Table 5 we present the means of size-adjusted abnormal returns for each decile-portfolio considering our entire sample, the results of the hedge portfolio test are based on December 31st fiscal-year-end firms-year. This arbitrary requirement is necessary once the hedge portfolio has to be assigned and maintained fixed during the test period. This procedure reduced our sample for $26,006$ firms-year observations. The means of other information for each decile-portfolio considering December 31st fiscal-year-end firms-year are presented in Table 5 (last two rows of Panel A).

[22] We also implemented this alternative procedure in estimating both abnormal accruals and other information. At this point, we required at least 10 firm-year observations for each time series regression, and only the last-year residual of each regression was considered as proxy for analysts' expectation of the impact of other information on next year earnings and abnormal accruals, respectively. This procedure, however, allow us to estimate other information and abnormal accruals only for firms-year that have past data available for at least 10 years. After these requirements, our sample size reduced to $19,971$ firm-year observations, in which $12,755$ have December 31st as fiscal-year-end. All our results remains qualitatively as the same.

and are also consistent with the accruals anomalies suggested by Xie (which indicate that the overpricing of abnormal accruals appear to be more severe than the overpricing of normal accruals). Our results, however, do not confirm the underprice of cash flows, as documented by Sloan (1996) and Xie (2001). In our case, the significance of the likelihood ratio statistic of cash flows suggests that the market also overprices the impact of cash flows on one-year-ahead earnings at 1% significance level. Note, however, that as our sample period accounts 20-years more recent data, there are no reasons to expect that the market continue pricing the impact of cash flows as in 20 years ago.

Panel A of Table 2 still presents the forecasting and valuation coefficients of other information. The valuation coefficient of other information is lower than the respective forecasting coefficient ($\gamma_4^* = 0.2473$ and $\gamma_4 = 0.4872$). As the likelihood ratio statistic indicates that these coefficients are not equal, we can not reject our hypothesis $H1(i)$. In summary, our preliminary results suggest that on average the market prices the persistence of earning components and other information according to its association with one-year-ahead earnings, but fail to distinguish the appropriate impact of cash flows, normal accruals, abnormal accruals, and other information on future earnings.

Panel B and C of Table 2 present results of the forecasting and valuation coefficients of earnings components and other information for the positive and negative other-information portfolios. Consistent with the anomaly of abnormal accruals documented by Xie (2001), our results suggest that the overpricing of abnormal accruals seems to be more severe than the overpricing of normal accruals in both portfolios. In the positive and in the negative domain of other information we also reject the null of market efficiency according to other information, since the null hypotheses $H_0 : \gamma_4 = \gamma_4^*$ are rejected at 1% and 5% significance level in respective portfolios. In the negative domain of other information, the valuation coefficient is larger than the forecasting coefficient ($\gamma_4^* = 0.7251$ and $\gamma_4 = 0.5860$). In this case, the significance at 5% of the likelihood ratio statistic suggests that the market on average overprices the impact of bad news on future earnings. On the other hand, in the positive domain of other information the valuation coefficient is lower than the forecasting coefficient ($\gamma_4^* = -0.4282$ and $\gamma_4 = 0.2179$). In this case, the significance at 1% of the likelihood ratio statistic suggests that the market on average underprices the impact of good news on future earnings.

The documented mispricing asymmetry between good and bad news is consistent with our prediction that the market gives on average more weight for other information that have an expected negative impact on future earnings than for other information that have an expected positive impact on future earnings. Our coefficients, actually, suggest that the market underprices the impact of good news and overprices the impact of bad news on future earnings. Given these results, we can not reject our hypothesis $H1(ii)$.

2.4.2 The Marginal Mispricing of Other Information

On Panel A, B, and C of Table 3 we present the results for the Mishkin test applied to the regression system composed by the forecasting equation 5 and the return equation 6, and for the OLS model described in equation 9, in order to empirically verify the equivalence between these methodologies[23]. The coefficients β of the return equations on Panel A, B, and C equal 1.0668, 1.2816, and 0.9573, respectively, and are all significants at 1% level.

[23]The results using the Mishkin test for our entire sample, and for the positive and negative other-information portfolios are identical to those reported on Table 2 (Panel A, B and C, respectively). We report it again for expositional convenience.

Table 2: **Market Pricing and Historical Persistence of Earnings Components and Other Information according to Its Implications on One-Year-Ahead Earnings**[a]

Panel A: Forecasting and Valuation Coefficients for the Entire Sample

Forecasting Coefficient			*Valuation Coefficient*			$H_0 : \gamma_i = \gamma_i^*$ [c]
Parameter[b]	Estimate	Std. Error	Parameter	Estimate	Std. Error	$P > \mathcal{X}^2$
γ_1(CFO$_t$)	0.4323***	0.0027	γ_1^*(CFO$_t$)	0.5224***	0.0211	0.0000
γ_2(NAC$_t$)	0.3224***	0.0044	γ_2^*(NAC$_t$)	0.4931***	0.0342	0.0000
γ_3(ABNAC$_t$)	0.2042***	0.0050	γ_3^*(ABNAC$_t$)	0.4095***	0.0386	0.0000
$\gamma_4(\widehat{V}_t)$	0.4872***	0.0064	$\gamma_4^*(\widehat{V}_t)$	0.2473***	0.0493	0.0000

Panel B: Forecasting and Valuation Coefficients for the Negative Other-Information Portfolio

Forecasting Coefficient			*Valuation Coefficient*			$H_0 : \gamma_i = \gamma_i^*$
Parameter	Estimate	Std. Error	Parameter	Estimate	Std. Error	$P > \mathcal{X}^2$
γ_1(CFO$_t$)	0.4690***	0.0040	γ_1^*(CFO$_t$)	0.5010***	0.0232	0.1720
γ_2(NAC$_t$)	0.3846***	0.0061	γ_2^*(NAC$_t$)	0.5053***	0.0358	0.0009
γ_3(ABNAC$_t$)	0.2457***	0.0070	γ_3^*(ABNAC$_t$)	0.4192***	0.0413	0.0000
$\gamma_4(\widehat{V}_t)$	0.5860***	0.0099	$\gamma_4^*(\widehat{V}_t)$	0.7251***	0.0578	0.0178

Panel C: Forecasting and Valuation Coefficients for the Positive Other-Information Portfolio

Forecasting Coefficient			*Valuation Coefficient*			$H_0 : \gamma_i = \gamma_i^*$
Parameter	Estimate	Std. Error	Parameter	Estimate	Std. Error	$P > \mathcal{X}^2$
γ_1(CFO$_t$)	0.3857***	0.0038	γ_1^*(CFO$_t$)	0.4849***	0.0361	0.0063
γ_2(NAC$_t$)	0.2463***	0.0064	γ_2^*(NAC$_t$)	0.3612***	0.0604	0.0584
γ_3(ABNAC$_t$)	0.1687***	0.0069	γ_3^*(ABNAC$_t$)	0.3722***	0.0665	0.0023
$\gamma_4(\widehat{V}_t)$	0.2179***	0.0105	$\gamma_4^*(\widehat{V}_t)$	-0.4282***	0.1076	0.0000

[a] Panel A, B and C present results obtained for the Mishkin test applied in our entire sample, and in the positive and negative other-information portfolios. These portfolios are formed annually by assigning firms which have their other information in the positive and negative domain, respectively.

[b] Variables definitions are present in Table 1. $*$, $**$, and $***$ represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

[c] Mishkin (1983) shows that the likelihood ratio statistics

$$2N \ln \left(\text{SSR}^c/\text{SSR}^u\right)$$

is asymptotically $\mathcal{X}^2$ distributed, under the null hypothesis that the market correctly prices the components of the rational forecast of one-year-ahead earnings. N represents the number of sample observations, and SSR^u and SSR^c represent the sum of squared residuals from the estimated regression system formed by equations 6 and 7, imposing any constraint and imposing the rational pricing constraints $\gamma_i = \gamma_i^*$, respectively.

The final column of each panel reports the coefficient $\phi_{i,\text{MT}} = \beta(\gamma_i - \gamma_i^*)$ obtained directly from the Mishkin test's estimated coefficients. As we expected, the calculated coefficients $\phi_{i,\text{MT}}$ and the estimated OLS coefficients ϕ_i are the same in all panels, for all $i = 1, ..., 4$. As we also expected, the significance of the OLS coefficients according to the t-test is consistent with the respective significance of the Mishkin test's likelihood ratio statistics. Therefore, in our setting, the OLS and the Mishkin test yield equivalent inferences.

On Table 4 we present results of the estimation of a model that includes a quadratic term and a dummy for negative values of other information, and also results for the estimation of the non-linear model 11, which includes quadratic terms and dummies for negative values of earnings components and other information.

In the first model, the estimated coefficient ϕ_{11} , ϕ_{12} and ϕ_{13} equal -0.0752, -0.1528 and -0.2059, respectively, and are both significants at 1% level. Consistent with our prior results, the interpretation of these coefficients suggest that the market overprices the persistence of cash flows, normal and abnormal accruals. According to other information, we find that all the coefficients ϕ_{j4}, j=1,...,4, are significants at 1% level. The significance of ϕ_{14} and ϕ_{34}, together with its positive and negative estimations of 1.2800 and -1.5722, respectively, suggest that the market underprices small good news and tends to overprice larger good news, since a negative value for ϕ_{34} indicates that ϕ_{14} decreases with the increase of the magnitude of positive other information. The significance of ϕ_{24} and ϕ_{44}, together with its negative and positive estimations of -1.3248 and 1.7582, respectively, and with the values of ϕ_{14} and ϕ_{34}, suggest that the market overprices bad news, and that this overprice tends to increase as the magnitude of the negative other information increase.

The estimated coefficients of the model 11 extend these analyses. Once the normal accruals coefficients ϕ_{j2}, $j = 1, 2, 3, 4$, are all non significants, we can not reject the null of market efficiency for positive and negative normal accruals. The analysis of the abnormal accruals coefficients ϕ_{j3}, $j = 1, 2, 3, 4$, however, suggests that the market correctly prices positive abnormal accruals, overprices negative abnormal accruals ($\phi_{23} = -0.6845$ is significant at 1% level), and that this overpricing seems to decrease with the magnitude of these accruals. These results for normal and abnormal accruals are consistent with the abnormal accruals anomalies documented by Xie (2001), but also suggest that the mispricing of abnormal accruals is due to negative abnormal accruals and decreases with the magnitude of these accruals.

According to the coefficients of cash flows, the significant and negative coefficient $\phi_{11} = -0.5556$ and the non-significant coefficient ϕ_{21} indicate that the market on average overprices the persistence of positive and negative cash flows at the same extent. The significant coefficients $\phi_{31} = 1.0783$ and $\phi_{31} + \phi_{41} = -0.1923$, however, suggest a reduction in the overpricing of both positive and negative cash flows, as the magnitude of these cash flows raises.

The results for other information also corroborate with our prior results. As ϕ_{14} and $\phi_{14} + \phi_{24}$ are positive and negative, and both significants at 1% level, we can not reject that the market underprices good news and overprices bad news. These results are consistent with our assumptions that the market gives a larger weight for bad news than for good news. The coefficients $\phi_{34} = -1.3248$ and $\phi_{34} + \phi_{44} = 0.3339$, however, are both significants at 1% level, suggesting that the overpricing of bad news increase with the magnitude of the expected impact of this information on one-year-ahead earnings, and that the market also tends to overprice the impact of good news when the expected impact of this information on future earnings

Table 3: **Mishkin Test and OLS Comparison**[a]

Panel A: OLS and Mishkin Test Coefficients for the Entire Sample[b]

Forecasting Coefficient		*Valuation Coefficient*		$H_0 : \gamma_i^* = \gamma_i$	*OLS Coefficient*		
Parameter	Estimate[c]	Parameter	Estimate	$\gamma_i^* - \gamma_i$	Parameter	Estimate	$\beta(\gamma_i - \gamma_i^*)$[d]
γ_1	0.4323***	γ_1^*	0.5224***	0.0901***	ϕ_1	-0.0961***	-0.0961
γ_2	0.3224***	γ_2^*	0.4931***	0.1707***	ϕ_2	-0.1822***	-0.1821
γ_3	0.2042***	γ_3^*	0.4095***	0.2053***	ϕ_3	-0.2190***	-0.2190
γ_4	0.4872***	γ_4^*	0.2473***	-0.2399***	ϕ_4	0.2559***	0.2559

Panel B: OLS and Mishkin Test Coefficients for the Negative Other-Information Portfolio

Forecasting Coefficient		*Valuation Coefficient*		$H_0 : \gamma_i^* = \gamma_i$	*OLS Coefficient*		
Parameter	Estimate	Parameter	Estimate	$\gamma_i^* - \gamma_i$	Parameter	Estimate	$\beta(\gamma_i - \gamma_i^*)$
γ_1	0.4690***	γ_1^*	0.5010***	0.0320	ϕ_1	-0.0411	-0.0410
γ_2	0.3846***	γ_2^*	0.5053***	0.1207***	ϕ_2	-0.1547***	-0.1547
γ_3	0.2457***	γ_3^*	0.4192***	0.1735***	ϕ_3	-0.2224***	-0.2224
γ_4	0.5860***	γ_4^*	0.7251***	0.1391**	ϕ_4	-0.1782**	-0.1783

Panel C: OLS and Mishkin Test Coefficients for the Positive Other-Information Portfolio

Forecasting Coefficient		*Valuation Coefficient*		$H_0 : \gamma_i^* = \gamma_i$	*OLS Coefficient*		
Parameter	Estimate	Parameter	Estimate	$\gamma_i^* - \gamma_i$	Parameter	Estimate	$\beta(\gamma_i - \gamma_i^*)$
γ_1	0.3857***	γ_1^*	0.4849***	0.0992***	ϕ_1	-0.0950***	-0.0950
γ_2	0.2463***	γ_2^*	0.3612***	0.1149*	ϕ_2	-0.1100*	-0.1100
γ_3	0.1687***	γ_3^*	0.3722***	0.2035***	ϕ_3	-0.1948***	-0.1948
γ_4	0.2179***	γ_4^*	-0.4282***	-0.6461***	ϕ_4	0.6185***	0.6185

[a] Panel A, B and C present results obtained for the Mishkin test applied to the regression system composed by the forecasting and the return equations, as described in the equations 6 and 7, and for the estimation of the equivalent OLS model described in equation 9.

Forecasting Equation : $\text{EARN}_{t+1} = \gamma_0 + \gamma_1\text{CFO}_t + \gamma_2\text{NAC}_t + \gamma_3\text{ABNAC}_t + \gamma_4\widehat{V}_t + e_{t+1}$

Return Equation: $\text{ABRET}_{t+1} = \alpha + \beta\left(\text{EARN}_{t+1} - \gamma_0^* - \gamma_1^*\text{CFO}_t - \gamma_2^*\text{NAC}_t - \gamma_3^*\text{ABNAC}_t - \gamma_4^*\widehat{V}_t\right) + \epsilon_{t+1}$

OLS Equation: $\text{ABRET}_{t+1} = \phi_0 + \phi_1\text{CFO}_t + \phi_2\text{NAC}_t + \phi_3\text{ABNAC}_t + \phi_4\widehat{V}_t + u_{t+1}$

[b] Variables definitions are present in Table 1.

[c] $*$, $**$, and $***$ represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

[d] The coefficient β of the return equations of Panel A, B and C equals 1.0668, 1.2816, and 0.9573, respectively, and are all significants at 1% level.

Table 4: **Non-Linear LS Model with Quadratic Terms and Dummies for Negative Earnings Components and Negative Other Information**[a]

Pooled OLS Regression for the Entire Sample[b]

Variable[c]	Parameter[d]	Estimate[e]	Std. Error	$P > \|t\|$	Estimate	Std. Error	$P > \|t\|$
CFO$_t$	ϕ_{11}	-0.0752***	0.0227	0.001	-0.5556***	0.1034	0.000
D_1CFO$_t$	ϕ_{21}				0.1956	0.1379	0.156
CFO$_t^2$	ϕ_{31}				1.0783***	0.2426	0.000
D_1CFO$_t^2$	ϕ_{41}				-1.2706***	0.2398	0.000
NAC$_t$	ϕ_{12}	-0.1528***	0.0363	0.000	-0.1012	0.2135	0.636
D_2NAC$_t$	ϕ_{22}				-0.2940	0.2452	0.231
NAC$_t^2$	ϕ_{32}				-0.4822	0.5610	0.390
D_2NAC$_t^2$	ϕ_{42}				0.3351	0.5573	0.548
ABNAC$_t$	ϕ_{13}	-0.2059***	0.0407	0.000	-0.0944	0.1230	0.443
D_3ABNAC$_t$	ϕ_{23}				-0.6845***	0.1693	0.000
ABNAC$_t^2$	ϕ_{33}				0.2826	0.2761	0.306
D_3ABNAC$_t^2$	ϕ_{43}				-0.7208***	0.2766	0.009
V$_t$	ϕ_{14}	1.2800***	0.1378	0.000	0.9718***	0.1406	0.000
D_4V$_t$	ϕ_{24}	-1.3248***	0.1979	0.000	-0.7270***	0.2052	0.000
V$_t^2$	ϕ_{34}	-1.5722***	0.2773	0.000	-1.3248***	0.2781	0.000
D_4V$_t^2$	ϕ_{44}	1.7582***	0.2975	0.000	1.6587***	0.2972	0.000
	ϕ_0	0.0531***	0.0055	0.000	0.0620***	0.0104	0.000
Number of Obs.		41,243			41,243		
F Statistic		24.85***			22.61***		
Adj R-squared		0.40%			0.83%		

[a] This table presents results for the estimation of the non-linear LS model described in equation 11.

$$\text{ABRET}_{t+1} = \phi_0 + \sum_{i=1}^{4}[\phi_{1i}X_i + \phi_{2i}D_iX_i + \phi_{3i}X_i^2 + \phi_{4i}D_iX_i^2] + \epsilon_{t+1}$$

X_1, X_2, X_3, and X_4 represent CFO$_t$, NAC$_t$, ABNAC$_t$, and $\widehat{V}_t$, respectively. D_i is a variable dummy set as 1 if X_i is negative, and 0, otherwise.

[b] Our sample is identified by merging firms listed on Compustat and I/B/E/S over 1983 to 2012. Monthly returns data were obtained on CRSP database. In the end, we obtained a sample size of $41,243$ observations over our 30-year sample period.

[c] Variable definitions are present in Table 1.

[d] Based on the interpretation of the OLS coefficients, the estimated coefficients $\phi_{41}, \phi_{42}, \phi_{43}$, and ϕ_{44} lead intuitively a graph for the average market function analogously of the hypothetical graph reported on Figure 1.

[e] $*$, $**$, and $***$ represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

is sufficiently large. These results support the characteristic $c)$ of our theoretical market function.

Together, these results allow us to make empirical inferences about the variation and marginal variation of our theoretical market function $\overline{V}_t$ (Equation 12) . As we expected, the theoretical characteristics $a)$, $b)$, and $c)$ are empirically satisfied, with $\overline{\lambda}_1 < 1$, $\overline{\lambda}_2 > 1$, $\overline{\lambda}_3 > 0$, and $\overline{\lambda}_4 > 0$. These results suggest that the market not only underprices (overprices) the persistence of positive (negative) other information, but tends also to overprice the impact of positive other information when the expected impact of this information on future earnings is sufficiently large.

2.4.3 Other Information and the Hedge Portfolio Test

The results of our non-linear model 11 presented on Table 4 suggest that the market acts as if it on average overprices the impact of bad news and large good news on future earnings. If the market overprices the impact of bad news and large good news on future earnings, then in the subsequent year the market should revalue stock prices in order to adjust for any prior mispricing of other information. In these cases, we would expect positive (negative) abnormal returns for firms-year in the extremes negative (positive) other-information decile portfolios one year after the portfolio formation.

The last two columns of Table 5 present the mean of size-adjusted abnormal returns for each other-information decile portfolio up to two years after the portfolio formation[24]. Decile portfolios are formed annually by ranking firms according to other information and assigning firms to decile based on the values of other information. As we expected, the lowest (highest) other-information decile portfolios experience positive (negative) size-adjusted abnormal returns in the subsequent year ($t + 2$), which is consistent with the results of our non-linear model 11. The distribution of the abnormal returns also suggest that the overpricing of bad news seem to increase with the magnitude of the expected impact of this information on next year earnings, and that the market also tends to underprice the impact of small good news and to overprice the impact of good news when the expected impact of this information on future earnings is sufficiently large.

Based on this non-linear market behavior, if a trading strategy taking a long position in firms with past negative other information, and a short position in firms with past positive other information yield positive abnormal stock returns, then the hedge-portfolio test would be providing evidences that the market overprices both large good and bad news in the portfolio formation year.

Although the last two columns of Table 5 present the means of size-adjusted abnormal returns for each other-information decile portfolio by considering all firms-year of our sample, we applied the hedge portfolio test only on December 31st fiscal-year-end firms-year. This requirement is necessary, once the hedge portfolio has to be assigned and maintained fixed during the buy-and-hold period. After imposing this requirement, our sample reduced to $26,006$ firms-year observations, in which $24,650$ and $23,240$ have non-missing size-adjusted abnormal returns for $t + 2$ and $t + 3$, respectively.

[24] The last two rows in Panel B of Table 5 presents the means os size-adjusted abnormal returns for each other-information decile portfolio considering the alternative estimation procedure. In this case, our sample size reduced to $19,971$ firm-year observations, in which $12,755$ have December 31st as fiscal-year-end. $11,447$ and $10,164$ December 31st fiscal-year-end firms-year have information about size-adjusted abnormal returns in $t + 2$ and $t + 3$, respectively.

The results of the last two columns of Table 5 (and results for December 31st fiscal-year-end firms-year[25]) review that the first two other-information decile portfolios lead size-adjusted abnormal returns of 20.38% (20.65%) and 14.68% (15.97%) in the year $t+2$, while the the last two other-information decile portfolios experience size-adjusted abnormal returns of -3.66% (-2.77%) and -5.42% (-3.51%), respectively, all significants at 1% level[26]. In $t+3$, the first two other-information decile portfolios still experience high size-adjusted abnormal returns of 16.50% (16.52%) and 13.98% (11.91%), all significants at 1% level, while the the last two other-information decile portfolios lead non-significants abnormal returns (for both entire and restricted sample).

Based on these abnormal returns, if we take long and short positions on the two-extreme negative and positive decile-portfolios, respectively, the hedge portfolio yields a high and significant abnormal gain of 21.45% in $t+2$, and 14.22% in $t+3$, both significants at 1% level. If we consider only the lowest and highest other-information decile portfolios, the hedge portfolio yields abnormal returns of 24.16% and 15.79% in the two following years, respectively, both significants at 1% level. Building the decile-portfolios according to other information obtained from the alternative procedure, the hedge portfolio yields a positive and significant abnormal gain of 14.46% in $t+2$, and 11.85% in $t+3$, both significants at 1% level. If we consider only the lowest and highest other-information decile portfolios, the hedge portfolio yields abnormal returns of 16.88% and 16.06% in the two following years, respectively, both significants at 1% level.

In order to explore the relation among other information, abnormal returns of $t+2$, and the association between other information and earnings of $t+2$, we estimate the following two-years-ahead earnings model

$$\text{EARN}_{t+2} = \beta_0 + \beta_1\text{CFO}_{t+1} + \beta_2\text{NAC}_{t+1} + \beta_3\text{ABNAC}_{t+1} + \beta_4\text{CFO}_t + \beta_5\text{NAC}_t + \beta_6\text{ABNAC}_t + \beta_7\widehat{V}_t + \beta_8 D.\widehat{V}_t$$

where D is a dummy set as 1 if V_t is negative, and 0, otherwise. If in controlling for past earnings components we find a positive incremental effect of other information on earnings of $t+2$, then this result would confirm that the market overprices other information in $t+1$. This implication follows once if good (bad) news that impacted earnings of $t+1$ are persistent and also have a positive (negative) incremental effect on earnings of $t+2$, then portfolios formed based on this information should also experience positive (negative) abnormal returns in $t+2$, conditional on the market correctly pricing this information in $t+1$.

Table 6 presents results for the estimation of this two-years-ahead earnings model using other information estimated from realized earnings[27] and obtained from the first and the alternative other information estimation procedure. Consistent with the market overpricing both good and bad news, the coefficients of positive and negative other information obtained from the first and the alternative estimation procedure are positive and significants at 1% level (β_7 equals 0.1272 and 0.2349, and $\beta_7+\beta_8$ equal 0.1272 and 0.0604, respectively), indicating that positive (negative) other information have a positive (negative) incremental effect on earnings of $t+2$, controlling for past earnings components.

As we find positive and negative abnormal returns for the lowest and highest portfolios in $t+2$ instead

[25] All abnormal returns for decile-portfolios based on December 31st fiscal-year-end firms-year are present in the last two rows of Panel A in Table 5.

[26] The abnormal return in $t+2$ of the highest decile-portfolio based on December 31st fiscal-year-end firms-year is significant at 5% level.

[27] Since at $t+2$ we know the earnings of $t+1$, we estimated the realized impact of other information on earnings of $t+1$ by replacing consensus analysts' forecast for realized earnings of $t+1$ in equation 14.

of negative and positive, respectively, we can not reject our hypothesis $H2$, in which a trading strategy taking long position in stocks of firms-year with past negative other information, and short position in stocks of firms-year with past positive other information generates positive size-adjusted abnormal returns in the subsequent year. Moreover, the hedge-portfolio test, together with the two-years-ahead earnings model's results, also present evidences that the market not only overprices bad news, but also overprices good news when the expected impact on future earnings of such news are sufficiently large.

Table 5 still presents the means of cash flows, normal accruals and abnormal accruals (set at the beginning of the fiscal year), and of other information and market value (set at the end of the fiscal year) for each other-information decile portfolio. Consistent with the correlation values presented on Panel B of Table 1, firms-year that experience on average high positive (negative) abnormal accruals in year t are likely to experience bad (good) news in the next year. An untabulated result also reviews that market value is positively correlated with other information. The means of market values present in the sixth column of Table 5 suggest that firms-year that experience good (bad) news on average experience an increase (reduction) in its market value in time, which is consistent with the linear pricing solution proposed by Ohlson (1995).

2.4.4 Other Information and Analysts' Consensus

Based on the presented evidences that the market act as if it does not understand (overprices) the impact of bad news and large good news contained in analyst forecasts, it seems not unreasonable to expect that this market-overpricing should be more severe when all analysts highlight and agree about the impact of such information on future earnings. In other words, if analysts have consensus about the impact of extreme other information on future earnings, the market is more likely to follow analysts. Therefore, firms-year subject to extreme news should be more likely to experience higher abnormal returns when analysts incorporate this information into their forecast and agree about the expected impact of such news on future earnings. In this subsection we apply the hedge portfolio test in portfolios formed by firms-year with high and low analyst forecast dispersion in order to confirm this prediction. By confirming our expectations, our results would provide evidences that the market misprices other information leading to arbitrage, which could be even larger when analysts agree about the expected impact of such information on future earnings.

Table 7 presents the mean of size-adjusted abnormal returns for portfolios formed by firms-year assigned to deciles based on the magnitude of the ranked other information, and on the magnitude of the ranked standard deviation of analysts' forecast (scaled by the respective mean of analysts' forecast), respectively. Rows indicate decile-portfolios based on other information and columns indicate decile-portfolios based on analysts' forecast dispersion. The lowest (highest) other-information decile indicates extreme negative (positive) other information, and the lowest (highest) analysts-forecast-dispersion decile indicates lowest (highest) analysts' forecast dispersion. As Brian and Tiras (2007), we consider the portfolios composed by firms-year situated in the last three analysts-forecast-dispersion deciles as portfolios situated in a poor information environment, and portfolios composed by firms-year situated in the first three analysts-forecast-dispersion deciles as portfolios situated in a good information environment.

Panel A and B of Table 7 present the means of abnormal returns for portfolios formed from the samples obtained when we considered our first and our alternative estimation procedure. On both Panels most part of the significant and positive abnormal returns are present in the negative domain of other information, are higher in the lowest decile of other-information, and even higher when analysts forecast dispersion is low. In the highest other-information decile portfolios, most of the significant abnormal returns are negative and are concentrated in the lower analysts-forecast-dispersion deciles.

Based on the abnormal returns present in Panel A (B) of Table 7, by forming a hedge portfolio taking long position in firms-year situated in the lowest and highest other-information decile portfolios, we obtain in the good information environment an abnormal return of 29.11% (13.59%), against a lower abnormal return of 5.37% (7.33%) in the poor information environment[28]. All these abnormal returns are significant at 1% level. Untabulated mean-comparison t-tests review that the abnormal returns obtained in the poor and in the good information environment are statistically different at 1% (10%) significance level.

These results corroborate with our prior evidences that the market overprices both extreme good and bad news, and with our prediction that this overpricing is more severe when analysts agree about the impact of such extreme news on future earnings. Our results also suggest the the overpricing of extreme bad news seems to be more severe than the overpricing of extreme good news. These evidences extend Brian and Tiras's (2007) results by suggesting that stock prices not only reflect information other than earnings, book value, and dividends contained in analysts' forecast, but also that the market overprices this information, specially when the expected impact of such news on future earnings are sufficiently large and analysts agree about it.

2.5 CONCLUSION

This paper analyses whether stock prices fully reflect the impact of other information contained in analysts' forecast according to its association with one-year-ahead earnings. Following Sloan (1996) and Xie (2001), we use the Mishkin test (1983) and the hedge-portfolio test to access this issue. Specifically, our assumption is that all news, which provide information about future earnings, determine revisions on current stock prices.

In our analyses, we attribute any mispricing of other information to the market's failure to correctly weigh this information according to its impact on one-year-ahead earnings. In order to justify this attribution, we presented a theoretical analysis of the relation among one-year-ahead earnings news, a hypothetical other information market weight function, the market expectation of the impact of other information, and the realized impact of this information as reflected in its association with one-year-ahead earnings. In particular, we claimed that the market reacts for both negative and positive other information, but gives more weight for bad news than for good news, which is consistent with the loss-aversion principle, as showed by Kahneman and Tversky (1979).

Based on the equivalence between the Mishkin test and a LS model in large samples, in order to make empirical inferences about the marginal variation of the market's mispricing of other information, and also to test if this market's mispricing holds as the magnitude of the impact of good and bad news on one-year-ahead earnings increase, we also considered a non linear model that contain a quadratic term

[28] In this case, the abnormal returns of the hedge portfolio test do not equal the mean of the returns of the respective portfolios presented on Table 5, since the number of firms-year of each double-characteristic portfolio are not the same.

and a dummy for negative values of other information. We also included in this non linear model quadratic terms and dummies for negative values of earnings components, in order to verify if the accruals anomaly documented by Xie (2001) increase or decrease with the magnitude of normal and abnormal accruals.

Empirical analyses confirm our predictions. As expected, other information are positively correlated with current returns and size-adjusted abnormal returns, and also with next year earnings, but not correlated with past earnings. Our analyses also review that good (bad) news on average increase (reduce) the firm's market value. This result is consistent with the linear pricing solution proposed by Ohlson (1995). The results of the Mishkin test suggest that the market acts as if it on average underprices the impact of good news and overprices the impact of bad news on future earnings, which is consistent with our assumption that the market gives on average more weight for bad news than for good news. The non linear analysis, however, reviews that the market not only underprices (overprices) the impact of positive (negative) other information, but tends also to overprice the impact of positive other information when the expected impact of this information on future earnings is sufficiently large.

Since size-adjusted abnormal returns are positively correlated with other information, on average firms with negative other information experience negative returns, and firms with positive other information experience positive returns. The hedge portfolio test shows that a trading strategy taking a long position in firms with past negative other information, and a short position in firms with past positive other information yields positive abnormal stock returns in the subsequent year. This result provides evidences that the market overprices extreme other information contained in analysts' forecast.

Our results also suggest that the overpricing of extreme news seems to be more severe for bad news over good news, and is higher when analysts highlight and agree about the impact of such news on future earnings. These evidences extend Brian and Tiras's (2007) results by suggesting that stock prices not only reflect information other than earnings, book value, and dividends provided by analysts, but also that the market overprices this information, specially when the expected impact of these news on future earnins are sufficiently large and analysts agree about it.

In summary, we extend the current literature by presenting evidences that the market does not correctly price the impact of other information contained in analysts' forecast, and also fails to price appropriately the impact of bad and good news on future earnings. Moreover, we provide evidences that the market overprices other information leading to arbitrage, which is larger when the expected impact of these news on future earnings are sufficiently large and when analysts agree about it.

According to the equivalence between the Mishkin test and OLS, although OLS is an easier method to implement and allows more straightforward comparisons among accounting researches, this method has a disadvantage according to it interpretation, since it depends on the signal and significance of the parameter β that cannot be estimated in the OLS model. If accounting researchers decide to use OLS, we suggest them to state more explicitly the theoretical reasons that support the signal and the significance of the coefficient β in their research settings or, alternatively, consider using both methods or only the Mishkin test.

This paper yields several issues for future researches. First, estimate other information using consensus analysts' forecast could cause a forecast bias, since analysts' forecast are not always accurate and some researches suggest that analysts are generally optimistic. Therefore it is still necessary a development of a better (unbiased) proxy for the market's expectation of the impact of other information on future earnings. Second, future researches could examine the relation between abnormal accruals and other information in a conservative accounting system, also investigating when the overpricing of abnormal accruals are due to discretionary managerial behavior or unusual economic circumstances. Finally, although OLS allows us to implement extra analyses that are difficult to be implemented by using the Mishkin test, it is still difficult to completely rule out unknown risk factors that could affect our results, specially in environments with high information asymmetry and low earnings quality. Restructure the Ohlson's (1995) information dynamic in order to adjust for heterogeneous belief, information asymmetry, and low earnings quality is still an open research question.

2.6 APPENDIX

2.6.1 The Equivalence between the Mishkin Test and LS in Non-Linear Models

In non-linear models, it is not easy to test the null hypothesis of market efficiency using the Mishkin test, once the statistic used to compare the estimated coefficient is $\mathcal{X}^2$ distributed and depends of particular convergency criteria required in the second stage. However, the equivalence in large samples between the Mishkin test and OLS can be also verified for non-linear models, as we will briefly demonstrate for the particular non-linear regression system that follows below. An advantage in using the LS in this case is that we can use a t-test to test the null hypothesis of market efficiency. With this propose, consider for simplicity the following forecast and return equations:

$$\text{EARN}_{t+1} = \gamma_0 + \gamma_{14}\widehat{V}_t + \gamma_{24}D_4\widehat{V}_t + \gamma_{34}\widehat{V}_t^{\,2} + \gamma_{44}D_4\widehat{V}_t^{\,2} + e_{t+1} \tag{16}$$

$$\text{ABRET}_{t+1} = \alpha + \beta\left(\text{EARN}_{t+1} - \gamma_0^* - \gamma_{14}^*\widehat{V}_t + \gamma_{24}D_4\widehat{V}_t^{\,*} + \gamma_{34}^*\widehat{V}_t^{\,2} + \gamma_{44}^*D_4\widehat{V}_t^{\,2}\right) + \epsilon_{t+1} \tag{17}$$

where D_4 is a dummy set as 1 for negative other information, and 0, otherwise. In this case, the forecasting and valuation coefficients depend on $\widehat{V}_t$ and equal

$$\gamma_4 = \begin{cases} \gamma_{14} + 2\gamma_{34}\widehat{V}_t, & \text{if } \widehat{V}_t \geq 0 \\ (\gamma_{14} + \gamma_{24}) + 2(\gamma_{34} + \gamma_{44})\widehat{V}_t, & \text{if } \widehat{V}_t < 0 \end{cases} \qquad \gamma_4^* = \begin{cases} \gamma_{14}^* + 2\gamma_{34}^*\widehat{V}_t, & \text{if } \widehat{V}_t \geq 0 \\ (\gamma_{14}^* + \gamma_{24}^*) + 2(\gamma_{34}^* + \gamma_{44}^*)\widehat{V}_t, & \text{if } \widehat{V}_t < 0 \end{cases}$$

Replacing the forecasting equation 16 into the return equation 17, we get the following LS model[29]:

$$\text{ABRET}_{t+1} = \alpha + \beta(\gamma_0 - \gamma_0^*) + \phi_{14}\widehat{V}_t + \phi_{24}D_4\widehat{V}_t + \phi_{34}\widehat{V}_t^{\,2} + \phi_{44}D_4\widehat{V}_t^{\,2} + \epsilon_{t+1} \tag{18}$$

where $\phi_{j4} = \beta(\gamma_{j4} - \gamma_{j4}^*)$, for $j = 1, 2, 3$ and 4. As in our setting β is a non null and positive constant, test the null hypothesis $H_0 : \phi_{j4} = 0$ is equivalent to test the market efficiency hypothesis $H_0 : \gamma_{j4}^* = \gamma_{j4}$. Rewriting ϕ_{j4}, we find $(\gamma_{j4}^* - \gamma_{j4}) = \frac{-\phi_{j4}}{\beta}$ and, therefore, the market weight function could be written in this case as

$$\overline{\lambda} = 1 + \frac{\gamma_4^* - \gamma_4}{\gamma_4} = \begin{cases} 1 - \frac{\phi_{14} + 2\phi_{34}\widehat{V}_t}{\beta(\gamma_{14} + 2\gamma_{34}\widehat{V}_t)} & \text{if } \widehat{V}_t \geq 0 \\ 1 - \frac{(\phi_{14}+\phi_{24}) + 2(\phi_{34}+\phi_{44})\widehat{V}_t}{\beta[(\gamma_{14}+\gamma_{24}) + 2(\gamma_{34}+\gamma_{44})\widehat{V}_t]} & \text{if } \widehat{V}_t < 0 \end{cases} \tag{19}$$

[29]In equation 18, the term βe_{t+1} was omitted. Since β is a constant and by construction e_{t+1} was designed to be orthogonal to other information, this exclusion does not cause asymptotically any bias in the estimation of any coefficient.

Since the coefficient β and the forecasting coefficient γ_4 are positive constants, the interpretation for $\overline{\lambda}$ follows analogously to it prior interpretation, except that now it is given for each $\widehat{V}_t$ and depends on the signal and significance of ϕ_{j4}, instead of the distance between the valuation coefficient γ_{j4}^* and the forecasting coefficient γ_{j4}.

3 NEITHER OPTIMISTIC NOR PESSIMISTIC: THE ROLE OF ACCOUNTING FUNDAMENTALS AND OTHER INFORMATION ON ANALYST FORECAST ERRORS

Abstract

During the last years researchers have produced an array of empirical evidences that have long offered conflicting conclusions according to how biased are the information provided by analysts. One of the reasons for such empirical controversy is that too little is known in the literature about analysts' actual loss functions, and the usual methodologies thus leave unresolved the questions of what cause asymmetries in forecast errors distribution and to what extent analysts fully reflect public available information. In this paper we implement an approach that allow us to disaggregate analyst forecast errors into an error related with past accounting information and another error related with other information, in order to evaluate the extent in which analyst forecast errors are related with information from these two different sources. Our analyses lead to two conclusions: first, accurate forecasts can be done even when it is associated with large positive accounting errors and large negative other information errors. In other words, analysts are neither optimistic nor pessimistic: it depends on the type, the sign, and the magnitude of the information. Second, even when analysts are right, they might be wrong. In these cases, our results suggest that luck trumps skills.

3.1 INTRODUCTION

In a practical perspective, other information can be interpreted as all new information not yet accurate in the financial statement, but that have yet to have an impact on earnings. Among obvious candidates for other information, Myers (1999) posits a discovery of a new petroleum field, new patents, regulatory approval of a new pharmaco, new long-lived contracts, etc. These news are just few examples among an infinite number of other information that may affect firm's future performance and analysts' expectations of firm's future performance.

A study developed by researchers of University of Michigan based on more than 470,000 analyst reports and 18,000 conference call transcripts find that "financial analysts highlight information in reports that aren't mentioned on calls with corporate officers and flesh out issues given just brief mentions on the calls" (University of Michigan, 2014). "... this finding suggests that analysts frequently provide new information by discussing exclusive topics that were not referred to in the CC" (Allen Huang et al., 2014). Whether or not analysts fully reflect other information according to its association with earnings, however, is an issue that still requires empirical verification.

Some studies including Ali, Klein, and Rosenfeld (1992), Elgers and Murray (1992), Lo and Elgers (1998), Frankel and Lee (1998), Hughes, Liu, and Su (2008), Gode and Mohanram (2009), and So (2013) have attempted to develop approaches that intend to present better predictions of future forecast errors by discussing what information is reflected in these errors. The majority of these studies have focused on the relation among consensus analyst forecasts, past forecast errors, and firms's characteristics, or in approaches that shifts the focus toward the time-series prediction of future earnings using historical information contained in the financial statements. Although their results recognize the relevance of analyzing past forecast errors, firms's characteristics, and accounting information in explaining analyst forecast errors, the relation of "other information"[30] in the assessment of analysts' accuracy have not yet received due attention. The goal of our paper is implement an approach that allow us to evaluate the extent in which analyst forecast errors are related with accounting information and "other information".

In order to identify and test how accurate analysts are in processing accounting information and other information, we developed a methodology that disaggregate analyst forecast errors into an error related with past accounting information and another error related with other information. We base our analyst error disaggregation approach on the Ohlson's (1995) Linear Information Dynamic that links earnings, book value, dividends, and other information with expectations of future earnings. Our analyst error disaggregation approach fundamentally is based on the assumption that, conditional on a set of available accounting information and other information, in expectation, consensus analyst forecast errors should be zero (Unbiased Forecast Condition - UFC).

By considering the unbiased forecast condition, if analysts on average correctly forecast the persistence of earnings components, book value, and dividends, then the coefficients relating these accounting components to analysts' expectation of next year earnings should be proportional to the coefficients relating these components to next year earnings. But if we reject the null for any of these variables, then it would suggest that analysts do not fully incorporate the persistence of the respective component into their forecast. On the other hand, if analysts on average correctly forecast the impact of other information on future earnings, then analysts' expectations about the impact of other information on next year earnings and the realized impact of other information on next year earnings should be statistically equal. If we reject this null hypothesis, it would suggest that analysts do not fully forecast the impact of other information on earnings.

When analyzing analyst bias, studies including Abarbanell and Lehavi (2003) find that extreme unexpected accruals go hand in hand with observations in the cross-section that generate the tail asymmetry in analyst forecast errors distribution. Other studies including Zhang (2006) find that "greater information uncertainty predicts more positive (negative) forecast errors and subsequent forecast revisions following good (bad) news" (Zhang, 2006), suggesting that information uncertainty delays the absorption of information into analyst forecasts. Based on these evidences, we predict that as much uncertainty surrounds the firm according to unexpected accruals and the relevance of other information for future earnings, more noisier signals exists about firm's future earnings and more likely are analysts to unintentionally forecast large errors or in acting in their incentives[31] to release biased forecasts. Since in both cases analysts may have fewer reputational concerns in release unbiased forecasts, this prediction do not go against the concerns present in the literature about analysts' incentives to bias their forecasts.

In spite of some similarities among our descriptive statistics with the widely held beliefs among ac-

[30]Olhson (1995) theoretically derived the relation between other information and expectations of future earnings in a valuation context. His contribution comes from the modeling of the linear information dynamic, which allows expectations of future earnings to be expressed as a linear function of earnings, book value, dividends, and other value relevant events (other information), which bear upon future earnings independently of current or past earnings.

[31]Some studies including Dugar and Nathan (1995), Das, Levine, and Sivaramakrishnan (1998), Lin and McNichols (1998), Michaely and Womack (1999), and Dechow, Hutton, and Sloan (2000) present concerns about the significant incentive misalignment between analysts and investors. The collective evidence from this literature suggests that analysts have incentives to bias their forecasts, which may originate from agency problems involving the relationship between securities firms and their clients, analysts' dependence on managers for information, among others.

counting and finance academics about analysts generally producing optimistic forecasts, analyses associated with the distribution of forecast errors of other information raises doubts about this conclusion. In our analyses, far more extreme other information (accounting) forecast errors of greater magnitude are observed in the ex-post "pessimistic" ("optimistic") tail of the distribution rather than in the "optimistic" ("pessimistic") tail. These characteristics of the distributions of accounting and other information forecast errors suggest that analysts may have different behaviors in forecasting the persistence of accounting data and the impact of new information on earnings.

Our analyses lead to two conclusions. First, our results suggest that analysts are neither optimistic nor pessimistic: it depends on the type, the sign, and the magnitude of the information. In summary, our results review that analysts are on average optimistic according to the persistence of accounting information and that book value, normal accruals, and negative abnormal accruals are together the cause of this partial optimism. In the other information dimension, our results suggest that analysts seem to forecast positive other information not with optimism, but with pessimism, and that analysts are even more pessimistic according to good news in poor information environments, where analyst forecast dispersion is high. Second, our analyses present evidences that even when analysts are right, they might be wrong. In other words, accurate forecasts can be done even when it is associated with large positive accounting errors and large negative other information errors. In these cases, it seems that luck trumps skills.

In our theoretical framework we also show that our analysts' error disaggregation approach leads similar conclusions to those obtained in the Mishkin (1983) test. In the usual accounting settings, the Mishkin test is applied to test whether the market rationally[32] prices the persistence of accounting components according to its association with the rational forecast of future earnings (see Sloan (1996), Xie (2001), etc). With some modifications in the regression system commonly used in the Mishkin test, we obtained a similar test that allow us to verify if analysts rationally forecast future earnings. Since control for other-information related factors and unusual-accruals related factors in the assessment of the relation between analysts' forecast errors and analysts' interpretation of the persistence of accounting information and the impact of other information on earnings, respectively, is a hard task, our disaggregation methodology provides a parsimonious and less biased approach that specify the role of accounting fundamentals and other information on analysts' accuracy.

Our study contributes to the analyst literature by documenting the association of analyst forecast errors with information beyond the accounting fundamentals. Our results present evidences that corroborate with analysts being optimistic, but also evidences that suggest pessimism. In particular, when financial accounting reports are less informative, as reflected by high abnormal accruals, our results suggest that analysts are more likely to forecast large positive errors, but also generate additional private information that reduces average forecast errors.

The remaining of the article is organized as follows. In the next section we introduce our analyst forecast error disaggregation approach and our hypotheses. In section 3, we describe the sample selection

[32]The Mishkin (1983) test relies on test market efficiency. An efficient market is defined as one in which stock prices fully reflect all available information that have an effect on the firm's intrinsic value (Fama (1970, 1991)). Analogously, our approach relies on test the unbiased forecast condition. This condition is satisfied if, and only if, analysts' forecast on average fully reflect all available information that have an effect on earnings.

procedure and the empirical data. Section 4 provides our results. Finally, in section 5 we provide a summary and conclusions.

3.2 ANALYST ERROR DISAGGREGATION

In order to establish a theoretical link between analyst forecast errors and the respective impact of accounting information and other information on analyst forecasts, we base our analysis on Ohlson (1995), who models a linear information dynamic that links earnings, book value, dividends, and other information with expectation of future earnings. This dynamic is based on two stochastic AR(1) process, as summarized below:

$$x^a_{t+1} = wx^a_t + V_{t+1} + e_{1t+1}$$
$$V_{t+2} = \gamma V_{t+1} + e_{2t+2}$$

Abnormal earnings x^a_{t+1} are defined as earnings above a charge for the use of capital, and are estimated as $x^a_{t+1} = x_{t+1} - r.b_t$, where b_t and r represent book value and the cost of capital at period t, respectively. The persistence of the abnormal earnings and the persistence of the aggregate impact V_{t+1} of new information on one-year-ahead (abnormal) earnings are indicated by the parameters[33] w and γ, respectively. The terms e_{1t+1} and e_{2t+2} represent unpredictable variables with zero mean.

In this information dynamic, all new information must be not correlated with past (abnormal) earnings, since in aggregate its predicted value $E_t[V_{t+1}]$ do not depend on past (abnormal) earnings. The term V_{t+1}, indeed, is theoretically designed to summarize the impact of value relevant events, bearing upon future (abnormal) earnings independently of past (abnormal) earnings.

Using the abnormal earnings definition and considering that all changes in book value must bypass by the difference between earnings and dividends (Clean Surplus Relation), follows directly from the information dynamic that the predicted value of one year-ahead-earnings can be set as a linear function in terms of current earnings, book value, dividends, and other information, as summarized below (Ohlson, 1995):

$$E_t[x_{t+1}] = wRx_t + (1-w)(R-1)b_t - w(R-1)d_t + V_{t+1} \tag{20}$$

where R equals unity plus the cost of capital r. As analyst forecasts not only reflect information about future earnings beyond that conveyed by earnings, book value, and dividends, but also reflect the “stale”information concurrently conveyed by the accounting fundamentals (Brian and Tiras 2007), we base our analysis considering the theoretical equation 20. Specifically, we are interested in evaluate the extent in which consensus analyst forecast errors are related with other information.

Once V_{t+1} is designed to be not correlated with past accounting data, we proxy the impact of other information on analysts' forecast as the regression residual[34] of analysts' forecast on earnings, book value,

[33]The parameters w and λ are restricted to be non-negative and less than one in order to assure that the unconditional means of both abnormal earnings and other information equal zero. See Dechow et al. (1999) for further details about the (mis)specification of the linear information dynamic.

[34]This residual approach parallels Ohlson and Shroff's (1992) approach for identifying unexpected earnings (which is a function of new information) in reported earnings, and Manry et al.'s (2003) approach for identifying unexpected earnings in reported quarterly earnings. Since other information are theoretically designed to be not correlated with past accounting data, omit other information in estimating equation 20 does not cause any bias in the estimation of the coefficients.

and dividends[35]:

$$\widehat{V}_{t+1} = E_t[x_{t+1}] - \widehat{\beta}_1 x_t - \widehat{\beta}_2 b_t - \widehat{\beta}_3 d_t \tag{21}$$

where $E_t[x_{t+1}]$ represents analysts' expectation of next year earnings. Note, however, that the residuals of this regression reflect only the aggregate impact of other information expected by analysts, and not the realized impact of other information on next year earnings.

Following Tse and Yaansah (1999), we use realized future earnings as proxy for the perfect earnings forecast. In this case, the residual of realized earnings on past earnings, book value, and dividends must reflect on average the aggregate impact of all new information on earnings:

$$V_{t+1} = x_{t+1} - \widehat{\beta}_1^* x_t - \widehat{\beta}_2^* b_t - \widehat{\beta}_3^* d_t \tag{22}$$

As analysts make their forecasts considering accounting data and other information, the errors ϵ_{t+1} in the formulation of their expectations must result from analysts' failure to fully incorporate accounting information or/and other information into their forecasts. In other words, analyst errors ϵ_{t+1} could be disaggregated into two components: an error $e_{\mathsf{X}_{t+1}}$ related to analysts misinterpreting the persistence of accounting data, and an error $e_{V_{t+1}}$ related to analysts misunderstanding the impact of other information on earnings:

$$\epsilon_{t+1} = e_{\mathsf{X}_{t+1}} + e_{V_{t+1}} \tag{23}$$

Once V_{t+1} is designed to be not correlated with past accounting data, follow from equations 21 and 22 that analysts' error ϵ_{t+1} and analysts' bias can be written as

$$\epsilon^i_{t+1} = E_t[x^i_{t+1}] - x^i_{t+1} = \left[(\widehat{\beta}_1 - \widehat{\beta}_1^*)x^i_t + (\widehat{\beta}_2 - \widehat{\beta}_2^*)b^i_t + (\widehat{\beta}_3 - \widehat{\beta}_3^*)d^i_t\right] + \left[\widehat{V}^i_{t+1} - V^i_{t+1}\right] = e^i_{\mathsf{X}_{t+1}} + e^i_{V_{t+1}} \tag{24}$$

$$\text{Bias}_{t+1} = \frac{1}{N}\sum_{i=1}^{N}\epsilon^i_{t+1} = \frac{1}{N}\sum_{i=1}^{N}\left(E_t[x^i_{t+1}] - x^i_{t+1}\right) = \frac{1}{N}\sum_{i=1}^{N}\left(e^i_{\mathsf{X}_{t+1}} + e^i_{V_{t+1}}\right) = \overline{e}_{\mathsf{X}_{t+1}} + \overline{e}_{V_{t+1}} \tag{25}$$

If analysts correctly forecast the impact of earnings, book value, and dividends on future earnings, then the estimated coefficient $\widehat{\beta}_i$ should be proportional to the estimated coefficient $\widehat{\beta}_i^*$, $i = 1, 2, 3$, respectively. But if the coefficient β_i relating an accounting component to analysts' expectation of next year earnings is not statistically equal to the coefficient β_i^* relating this component to next year earnings, then the respective null will be rejected. In other words, it would suggest that analysts would be failing to fully incorporate the persistence of this accounting information into their forecast. On the other hand, if analysts on average correctly forecast the impact of other information on future earnings, then analysts' expectations of the impact of other information on next year earnings and the realized impact of other information on next year earnings should be proportional. If we reject this null hypothesis, it would suggest that analysts could be misunderstanding the impact of other information on earnings.

In terms of persistence of the accounting components and the impact of other information on earnings, the expressions overestimate and underestimate can be related with both positive and negative forecast errors, depending on the sign of the respective accounting component or of the other information. Table 8 illustrates each possible situation by using a variable with a hypothesised persistence that equals

[35]Brian and Tiras (2007) uses the cross section regression residual of consensus analyst forecasts (median of analysts' forecast) on book value and earnings after dividends as proxy for other information.

one. Note that overestimation (underestimation) is related with an estimated persistence statistically greater (smaller) than one in both types of impacts on earnings (positive and negative), but not with the same sign of analyst forecast errors. In terms of dividends, for example, if analysts overestimate the impact of the dividends distribution policy on earnings, then the effect of analysts' interpretation of the impact of dividends on future earnings would be greater than the realized impact. In this case, even if analyst forecasts are on average greater than realized earnings (positive forecast errors), the contribution of analysts' interpretation of the impact of the dividends distribution policy on forecast errors would be negative.

Regress analyst forecast errors on earnings, book value, and dividends allow us to test if analysts on average correctly forecast the impact of accounting information on next year earnings:

$$\epsilon^i_{t+1} = \phi_0 + \phi_1 x_t + \phi_2 b_t + \phi_3 d_t + u_{t+1} \tag{26}$$

This implication follows directly from the comparison between equations 24 and 26: test the null hypotheses $H^i_0 : \beta_i - \beta^*_i = 0$ is equivalent to test the null hypotheses $H^i_0 : \phi_i = 0$, $i = 1, 2, 3$, respectively.

If analysts present lack of skills in interpreting information or have incentives to forecast with bias the time-series predictable component of next-year earnings or the expected impact of other information on next-years earnings, then at least one estimated coefficient $\widehat{\beta}_i$ should be disproportional to the respective estimated coefficient $\widehat{\beta}^*_i$, $i \in \{1, 2, 3\}$, and/or $E[\widehat{V}_{t+1}] - V_{t+1}$ should be on average different than zero, respectively. In these cases, we should have

$$\widehat{\beta}_i = \beta_i + f_{it+1} + \xi_{it+1} \quad \Rightarrow \quad E[\widehat{\beta}_i] \neq \beta_i \tag{27}$$

and/or

$$\widehat{V}_{t+1} = V_{t+1} + g_{Vt+1} + \xi_{Vt+1} \quad \Rightarrow \quad E[\widehat{V}_{t+1}] \neq V_{t+1} \tag{28}$$

where ξ_{it+1} and ξ_{Vt+1} are unpredictable zero mean terms, and f_{it+1} and g_{Vt+1} are function based on analysts' lack of skills (LSKILLS) and analysts' incentives (INC) to issue biased forecasts according to the component X_i and other information, respectively. Without loss of generality, we can assume

$$f_{it+1} = \rho_1 \text{LSKILLS}_{it+1} + \rho_2 \text{INC}_{it+1}, \quad \text{corr}(\text{LSKILLS}_{it+1}, \text{INC}_{it+1}) = 0$$

and

$$g_{Vt+1} = \varphi_1 \text{LSKILLS}_{Vt+1} + \varphi_2 \text{INC}_{Vt+1}, \quad \text{corr}(\text{LSKILLS}_{Vt+1}, \text{INC}_{Vt+1}) = 0$$

In terms of other information, analyse the residual u_{t+1} is not sufficient to test if analysts on average correctly forecast the impact of other information on next year earnings. It follows once the constant ϕ_0 may be capturing both analysts' incentives to bias other information or other analysts' incentives, as bias originated from agency problems involving the relationship between securities firms and their clients, analysts' dependence on managers for information, among others. However, as expected other information and realized other information should be proportional in case of analysts correctly forecasting the impact of other information on earnings, than the coefficient relating expectations and realizations should equal one. The following regression allow us to test if analysts on average correctly forecast the impact of other information on earnings:

$$\widehat{V}_{t+1} = \rho_0 + \rho_1 V_{t+1} + \epsilon_{t+1} \tag{29}$$

3.2.1 A Reformulated Mishkin Test

Another approach that leads similar conclusions to those obtained in the model 26 can be set by implementing the Mishkin (1983) test in our framework. In the usual accounting settings, the Mishkin test is applied to test whether the market rationally prices the persistence of accounting components according to its association with the rational forecast of future earnings (Sloan (1996), Xie (2001), Kraft et al. (2007), etc). With some modifications in the regression system commonly used, we can test if analysts rationally incorporate past accounting information into their forecasts. Our reformulated Mishkin test approach starts from the basic implication that, conditional on a set of information Θ available at the end of period $t+1$, in expectation, consensus analyst forecast errors should be zero (Unbiased Forecast Condition - UFC). It means that

$$E[E_t[x_{t+1}] - x_{t+1}|\Theta] = 0 \tag{30}$$

where $E_t[x_{t+1}]$ represents analysts' consensus of next year earnings.

If $K = \{K_1, K_2, ..., K_n\}$ is a set of relevant variables that explain next year earnings, then a model that satisfies the unbiased forecast condition, conditional on the set of information Θ, is

$$(E_t[x_{t+1}] - x_{t+1}) = \alpha + \delta\left(x_{t+1} - E_t^K[x_{t+1}|\Theta]\right) + h_{t+1} \tag{31}$$

where α is a constant, δ is a forecasting multiplier, h_{t+1} is a disturbance with zero mean conditional on the set of information Θ, and $E_t^K[x_{t+1}|\Theta]$ is the rational forecast of x_{t+1} at time t based on the set of variables K and conditional on the set of information Θ, which is set as

$$E_t^K[x_{t+1}|\Theta] = \gamma_0^* + \gamma_1^* K_1 + \gamma_2^* K_2 + ... + \gamma_n^* K_n$$

In our analysis we attempt to split the set of relevant variables K into two independent set of information: $X^{t+1} = \{X_{1t}, X_{2t}, ..., X_{Mt}\}$, where X_{it} represents an accounting information i that is relevant to explain future earnings, and $V^{t+1} = \{v_{1t+1}, v_{2t+1}, ..., v_{Nt+1}\}$, where v_{jt+1} represents a news j that have an impact V_{jt+1} on earnings of $t+1$. Follows that

$$E_t^K[x_{t+1}|\Theta] = E_t^X[x_{t+1}|\Theta] + E_t^V[x_{t+1}|\Theta] = \gamma_0^* + \gamma_1^* X_1 + \gamma_2^* X_2 + ... + \gamma_M^* X_M + \gamma_{M+1}^* V_1 + \gamma_{M+2}^* V_2 + ... + \gamma_{M+N}^* V_N$$

As in our setting we are using past earnings[36], book value, and dividends to summarize the persistence of past performance on future earnings, we must have:

$$E_t^X[x_{t+1}|\Theta] = \gamma_0^* + \gamma_1^* \mathsf{x}_t + \gamma_2^* \mathsf{b}_t + \gamma_3^* \mathsf{d}_t \tag{32}$$

Based on equation 31 and on the framework presented, the regression system of the Mishkin test to be estimated is composed by the following equations[37]:

$$x_{t+1} = \gamma_0^* + \gamma_1^* \mathsf{x}_t + \gamma_2^* \mathsf{b}_t + \gamma_3^* \mathsf{d}_t + h_{1t+1} \tag{33}$$

[36] As information contained in cash flows, normal and abnormal accruals have different persistence according to future earnings, we will consider earnings components instead of total earnings in our empirical analyses. In our theoretical approach we use total earnings for expositional convenience without loss of interpretation.

[37] Equations 33 and 34 are estimated jointly using a two stages iterative generalized non linear least square estimation procedure, as in Mishkin (1983).

$$\epsilon_{t+1} = \alpha + \delta\left(\mathsf{x}_{t+1} - \gamma_0 - \gamma_1 \mathsf{x}_t - \gamma_2 \mathsf{b}_t - \gamma_3 \mathsf{d}_t\right) + h_{2t+1} \tag{34}$$

where $\epsilon_{t+1} = E_t[x_{t+1}] - x_{t+1}$ represents consensus analyst forecast errors, and the other variables are defined as before.

In this case, if analysts on average correctly forecast the impact of a component X_i on future earnings, then the analyst forecast coefficient γ_i should be proportional to the rational forecast coefficient γ_i^*. In other words, under the unbiased forecast condition, analysts should forecast the persistence of the component X_i on next year earnings proportionally to the coefficient that relates this component to future earnings. On the other hand, if the coefficient γ_i that relates analysts' forecast to future earnings is not statistically equal to the coefficient that relates the component X_i to future earnings, then the null will be rejected. In this case, it would indicate that analysts on average do not fully incorporate the persistence of the component X_i into their forecasts.

Mishkin (1983) showed that the rational forecast coefficient γ_i^* and the analyst forecast coefficient γ_i can be statistically compared by the likelihood ratio $\mathcal{X}^2(i) = 2T\ln(\text{SSR}^c/\text{SSR}^u)$, which is asymptotically $\mathcal{X}^2$ distributed. T represents the number of sample observations, and SSR^u and SSR^c represent the sum of squared residuals from the estimated regression system formed by equations 33 and 34, imposing any constraint and imposing the unbiased forecast constraint $\gamma_i^* = \gamma_i$, respectively.

Mishkin (1983) and Abel and Mishkin (1983a) also demonstrate that the parameter estimates and the statistics of test between the Mishkin test and an analogous OLS model are asymptotically equivalent[38]. Based on equivalent arguments, we can briefly demonstrate that our reformulated Mishkin test and model 26 leads similar conclusions. Indeed, replacing the forecasting equation 33 into the analyst equation 34, we get the following model

$$\epsilon_{t+1}^i = \alpha + \delta(\gamma_0^* - \gamma_0) + \psi_1 x_t + \psi_2 b_t + \psi_3 d_t + \delta h_{1t+1} + h_{2t+1} \tag{35}$$

where $\psi_i = \delta(\gamma_i^* - \gamma_i)$, with $i = 1, 2, 3$. As β is a non null constant, test the null hypothesis $H_0 : \psi_i = 0$ is equivalent to test the rational forecast condition hypothesis $H_0 : \gamma_i^* = \gamma_i$. In our setting, a ψ_i statistically equal to zero indicates that analysts fully incorporate the persistence of the component X_i according to its association with one-year-ahead earnings. But if ψ_i is statistically negative (positive), then the t-test would indicate that[39] on average analysts underestimate (overestimate) the impact of the component X_i on earnings.

In spite of theoretical design, models 26 and 35 are equivalents[40]. In fact, the coefficients $\phi_i = (\beta_i - \beta_i^*)$ of the model 26 and the coefficients $\psi_i = \delta(\gamma_i^* - \gamma_i)$ of the model 35 are the same. Moreover, the

[38] Abel and Mishkin (1983a) show that this equivalence hold not only asymptotically, but also for finite samples, after some adjustments for degrees of freedom.

[39] Although model 26 is easier to implement and allows more straightforward comparisons among accounting researches, this methodology has a disadvantage according to its interpretation. On one hand, if δ is not significant, we cannot make any inference about the relation between analyst forecast errors and the residuals of the forecasting equation. On the other hand, if β is negative, then a negative (positive) coefficient ψ_i would indicate that analysts underestimate (overestimate) the impact of the respective component X_i on earnings, instead of overestimate (underestimate) it. If accounting researchers decide to use a test based on the model 26, we suggest them to state more explicitly the theoretical reasons that support the sign and the significance of the coefficient δ in their research settings or, alternatively, consider using both methods or only the Mishkin test.

[40] One of the disadvantages in using the reformulated Mishkin test approach over the analyst error disaggregation approach is that it does not allow us to access the distribution of other information contained in analysts' forecast.

error term $(\delta h_{1t+1} + h_{2t+1})$ in 35 is theoretically designed to summarize the extent in which the component of analyst forecast errors are related to information in V^{t+1} beyond the information in X^{t+1}, as in the error component $u_{t+1} = \widehat{V}_{t+1} - V_{t+1} = e_{V_{t+1}}$ of the model 26.

In the following sections we use our analyst error disaggregation approach to investigate to what extent analyst forecast errors are related with accounting information and other information. Specifically, we are interested in how related are the level of uncertainty in the firm's environment with the portion of analyst forecast errors related with other information, and the quality of past earnings (accruals) with the portion of analyst forecast errors related with information contained in past financial statements.

Once past-accounting-basis forecast requires analysts to estimate future earnings basing on firm's past performances, earnings with low quality are likely to provide noisier signals about firm's future earnings, leading to information asymmetry among managers, analysts, and the market. If past earnings provide less precise signals about firm's future earnings, we expect that analyst forecast errors related to the predictable time series component of earnings are likely to increase. Abarbanell and Lehavi (2003) present some evidences consistent with this prediction by identifying an empirical link between the recognition of unexpected accruals and the asymmetries in the distribution of analyst forecast errors. Bradshaw et al. (2001) also show that "analysts' forecast do not incorporate the predictable future earnings declines associated with high accruals" (Bradshaw et al., 2001).

On the other hand, studies including Zhang (2006) find that "greater information uncertainty predicts more positive (negative) forecast errors and subsequent forecast revisions following good (bad) news" (Zhang, 2006), suggesting that information uncertainty delays the absorption of information into analyst forecasts. In this case, we expect that analyst forecast errors related to other information increase when firms are subject to an uncertain economic environment.

3.3 SAMPLE SELECTION PROCEDURE AND EMPIRICAL DATA

Our sample was initially identified by merging firms listed on Compustat and I/B/E/S over 1983 to 2012. Book value, dividends, and other financial data were obtained from Compustat. Consensus analyst forecasts and actual earnings were obtained on I/B/E/S. We excluded firms with negative book value and firms from regulated financial institutions and utilities (SIC codes between 6000 and 6999). Observations with missing Compustat data, or missing analyst forecasts and actual earnings were also deleted. As we estimate other information in panel regression by 4-digit SIC code, we restricted our sample for sectors that have firms with all the required data available, with a minimum of 30 observations per sector during the sample period. Observations with consensus forecast errors exceeding in absolute value 100 percent of actual earnings were also excluded, since these observations seem to result from a data input error. After these requirements, we obtained a sample size of $40,660$ firms-year over our 30-years sample period. To enhance comparability with other studies, we also winsorized all variables yearly at 1% and 99% level.

In our analysis, earnings ACTUAL$_t$ are defined as IBES actual earnings, book value BV$_t$ is set as total common equity (Compustat item $\#60$), and DIV$_t$ represents total dividends paid at the end of each fiscal year (sum of Compustat items $\#19$ and $\#21$, plus dividends other than stock dividends declared on other share capital of the company and based on the current year's net income). CAF$_t$ represents consensus analysts forecast set as the mean[41] of all forecasts made in the period between the fiscal-year-end and the earnings announcement date.

Following Sloan (1996), total accruals TAC_t are measured by the difference between earnings before extraordinary items EARN_t (Compustat item $\#18$), and cash flow from operating activities CFO_t, reported under SFAS no.95 (Compustat item $\#308$), i.e.,

$$\text{TAC}_t = \text{EARN}_t - \text{CFO}_t$$

For the period before 1988 when Compustat item $\#308$ is not available, we estimate cash flow as the sum of funds from operations FFO_t (Compustat item $\#110$), change in cash and short term investment ΔCASH_t (Compustat item $\#1$), and change in current liabilities ΔCL_t (Compustat item $\#5$), minus the change in short term debt ΔSTD_t (Compustat item $\#34$), and minus the change in current assets ΔCA_t (Compustat item $\#4$), as follows:

$$\text{CFO}_t = \text{FFO}_t + \Delta\text{CASH}_t + \Delta\text{CL}_t - \Delta\text{STD}_t - \Delta\text{CA}_t$$

As in Xie (2001), we consider normal accruals NAC_t as the predicted value of Jones (1991) model, estimated using a panel regression for each 4-digit SIC code:

$$\text{NAC}_t = \widehat{\text{TAC}}_t = \widehat{\alpha_0} + \widehat{\alpha_1}\Delta\text{REV}_t + \widehat{\alpha_2}\text{PPE}_t \tag{36}$$

where ΔREV_t represents changes in sales revenue in fiscal year t (Compustat item $\#12$), and PPE_t is gross property, plant, and equipment (Compustat item $\#7$). All variables were deflated by the beginning-of-fiscal-year total assets TA_{t-1} (Compustat item $\#6$). Abnormal accruals ABNAC_t are given by the residuals of the Jones (1991) model, i.e.,

$$\text{ABNAC}_t = \text{TAC}_t - \text{NAC}_t$$

We estimate analysts' expected impact of other information using a panel for each 4-digit SIC code by regressing consensus analyst forecasts on cash flow, normal accruals, abnormal accruals, book value, and dividends.

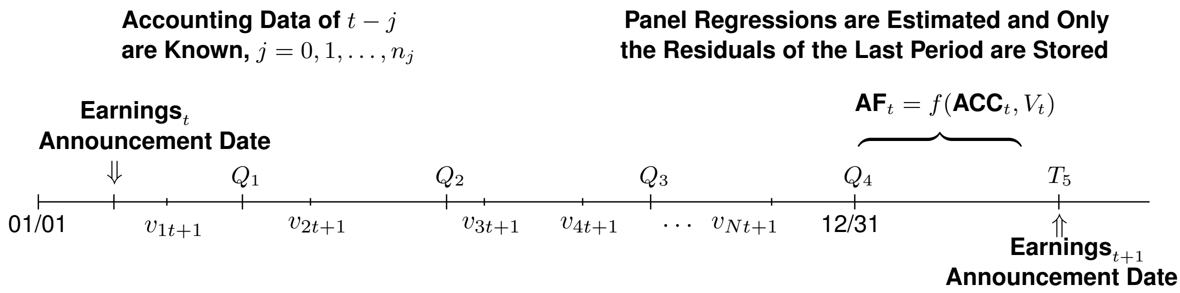
$$\widehat{V}_{t+1} = \text{CAF}_t - \widehat{\beta}_0 - \widehat{\beta}_1\text{CFO}_t - \widehat{\beta}_2\text{NAC}_t - \widehat{\beta}_3\text{ABNAC}_t - \widehat{\beta}_4\text{BV}_t - \widehat{\beta}_5\text{DIV}_t \tag{37}$$

Analogously, we use the residual of the panel regression of realized next year earnings on cash flow, normal accruals, abnormal accruals, book value, and dividends as proxy for the realized impact of other information on earnings:

$$\widehat{V}^*_{t+1} = \text{ACTUAL}_{t+1} - \widehat{\beta}^*_0 - \widehat{\beta}^*_1\text{CFO}_t - \widehat{\beta}^*_2\text{NAC}_t - \widehat{\beta}^*_3\text{ABNAC}_t - \widehat{\beta}^*_4\text{BV}_t - \widehat{\beta}^*_5\text{DIV}_t \tag{38}$$

In order to avoid any look-ahead-bias in estimating analysts' expected impact of other information, realized other information, and also abnormal accruals, we estimate each of our panel regression using a multi-panel procedure, in which for each year we associate a panel that contain only information of past years. In this case, only the residual of the last year is stored in each panel-year. In terms of other information, for example, if we do not use this multi-panel procedure, than we would require that analysts

[41] We also used the median of analysts' forecast in our analyses. All our conclusions follow qualitatively as the same.



known at the first years information about future years. The time line presented in the above diagram uses a firm-year with December 31st fiscal-year-end as an illustration of our research design[42].

Panel A of Table 1 presents descriptive statistics for the accounting fundamentals. The results are comparable to those reported on Xie (2001, Table 1, Panel A), regardless of differences in the sample period. Panel B presents descriptive statistics for realized other information $\widehat{V}^{*}_{t+1}$, expected other information $\widehat{V}_{t+1}$, consensus analyst forecasts CAF$_t$, buy-and-hold return RET$_{t+1}$, and size-adjusted abnormal return[43] ABRET$_{t+1}$.

Comparing realizations and expectations in terms of earnings, we find that the mean of analyst forecasts is statistically greater than the mean of actual earnings at 1% significance level over our 30-years sample period. This result is consistent with evidences present in the literature which suggest that analysts are generally optimistic (see, e.g., reviews by Brown, 1993; Das, Levine $\&$ Sivaramakrishnan, 1998; Lim, 2001; Kothari, 2001; and Cowen, Groysberg $\&$ Healy, 2006). In terms of analyst forecast errors, an untabulated t-test reviews that the mean of analyst forecast errors is greater than zero, which also corroborate with analysts overestimating future earnings.

In spite of the similarities among these descriptive results with the widely held beliefs among accounting and finance academics about analysts generally producing optimistic forecasts, summary statistics associated with forecast error distributions reported in Panel B of Table 1 raise doubts about this conclusion. It follows because, as in Abarbanell and Lehavy (2003), the only statistical indication that supports analyst optimism is a positive mean forecast error of 0.003. On the other hand, the median error is zero, which suggest unbiased forecasts, while the percentage of positive errors is smaller than the percentage of negative errors, which suggest an apparent analyst pessimism.

This apparent analyst pessimism can also be viewed when we analyse analysts' expectation of other information. As can be seen in Panel B of Table 1, the mean of realized other information is 0.021, while the

[42]We also estimate other information firm-by-firm in a time series regression, once the impact of new information on next year earnings must be affected by particular conditions like firm's economic pressure, production technology, and others firm's specific characteristics. Adding conditioning variables to control for these forces is difficult (Myers 1999). This procedure, however, reduces our sample to $19,971$ firms-year, since we required a minimum of 10 observations per firm in order to estimate each regression and only the last residual of each regression was stored (multi-time-series procedure). All our results follow qualitatively as the same.

[43]Following Sloan (1996), we estimate size-adjusted abnormal return as the difference between the firm's buy-and-hold return for the 12-month period ending three months after the fiscal-year-end, and the market's subjective expectation of the normal return set as the buy-and-hold return for the same 12-month period of the market-capitalization-based portfolio decile in which the firm belongs.

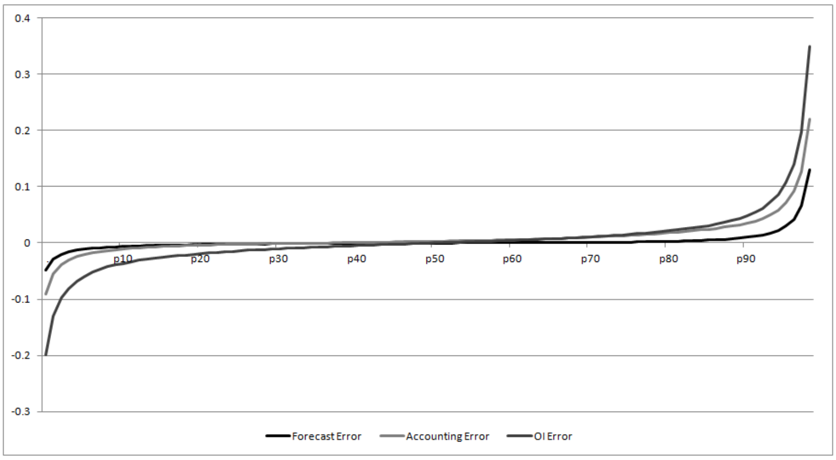


Figure 2: Plot comparison of the 1st through the 99th percentiles of the distributions of analysts' forecast errors, and of the disaggregated accounting and other information error components.

mean of analysts' expectation of other information is 0.015. An untabulated t-test review that the mean of analysts' expectation of other information is smaller than the realized other information at 1% significance level. At this point, the frequency of negative realized other information is smaller than the frequency of negative expected other information (39.69% vs 43.07%).

In order to better understand the causes of these inconsistencies in the summary statistics, we projected analysts forecast errors in the accounting dimension and in the other information dimension using our disaggregation approach. As can be seen in Panel B of Table 1, the mean of analyst forecast errors according to other information is negative (-0.006), while the mean of analyst forecast errors according to the accounting components is positive (0.009). Moreover, the frequency of positive analyst forecast errors according to the accounting components is greater than the frequency of positive analyst forecast errors according to other information (71.10% vs 31.97%). Untabulated t-tests also review that the mean of analyst forecast errors according to other information is smaller than zero, while the mean of analyst forecast errors according to the accounting fundamentals is greater than zero. Together, these descriptive results suggest that analysts seem to forecast other information not with optimism, but with pessimism, and that the analysts' optimism widely documented in the literature seem to be associated with accounting information.

Figure 2 presents a comparative plot of the 1st through the 99th percentiles of the distributions of analyst forecast errors ϵ_{t+1}, of the accounting forecast error component $\epsilon_{X_{t+1}}$, and of the other information forecast error component $\epsilon_{V_{t+1}}$ over the sample period. Moving from left to right, forecast errors and forecast error components range from the most negative to the most positive values. As can be seen in Figure 2, a distinctive feature of the distributions is that for the other information error component and for the accounting error component, the left and the right tails are longer and fatter than the respective tail of the distribution of analyst forecast errors. Moreover, these asymmetries seem to be more apparent in the negative tail for the other information error component and in the positive tail for the accounting error component. In these cases, it suggest that far more extreme accounting (other information) forecast errors of greater absolute magnitude are observed in the ex-post “optimistic” (“pessimistic”) tail of the distribution than in the “pessimistic” (“optimistic”) tail.

Figures 3 and 4 present a comparison of the histogram of analyst forecast errors with the histogram of each disaggregated error component. A closer inspection of the graphics reveals that analysts seem to be more pessimistic (optimistic) in forecasting the impact of other information (accounting information) on future earnings, which corroborate with the the doubts raised by our descriptive statistic. These characteristics of the distributions suggest that analysts may have different behaviors in forecasting the persistence of accounting data and the impact of new information. It is not clear, however, if this apparent analyst pessimism according to other information have been driven by analysts overestimating negative other information or underestimating positive other information. In the next section we provide further analyses in order to test if analysts fully reflect the accounting fundamentals and other information, and how these forecasts are affected by earnings (accruals) quality and information asymmetry, respectively.

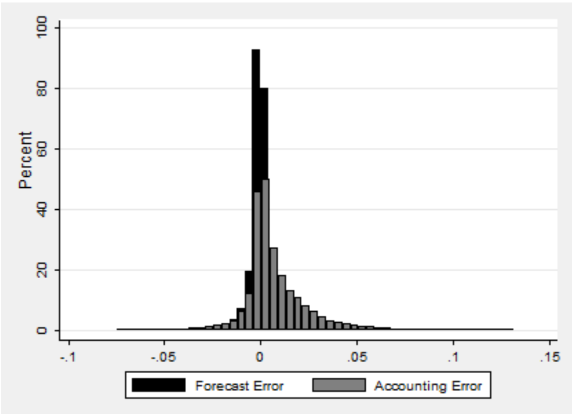


Figure 3: Histograms of analyst forecast errors and of the accounting error component.

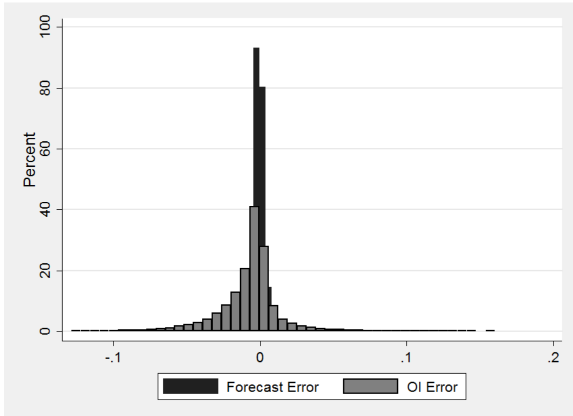


Figure 4: Histograms of analyst forecast errors and of the other information error component.

3.4 EMPIRICAL RESULTS

In this section we provide further analyses about accounting forecast errors and other information forecast errors. We use our analyst error disaggregation approach to investigate to what extent analyst forecast errors are related with accounting information and other information. At this point, we first estimate models 26 and 29 in order to test if analysts fully reflect the accounting fundamentals and other information. Then, we divide firms into groups with low and high abnormal accruals, and with low and high analyst forecast dispersion, in order to verify how these forecasts are affected by information quality. Specifically, we are interested in how related are the level of uncertainty in the firm’s environment with the portion of analyst forecast errors related with other information, and the quality of earnings (accruals) with the portion of analyst forecast errors related with information contained in past financial statements.

3.4.1 The Impact of Accounting Information on Inferences Concerning Analyst Bias

Panels A, B, and C of Table 10 present the results for the estimated coefficients of the reformulated Mishkin test and of the model 26 for the entire sample and for portfolios based on positive and negative abnormal accruals. The coefficient δ of the analyst equation 34 is negative in all Panels, once we defined analyst forecast errors as the difference between consensus analyst forecasts and actual earnings.

The final column of each panel reports the coefficient $\delta(\gamma_i^* - \gamma_i)$ obtained directly from the coefficients of the Mishkin test. As expected, the calculated coefficients $\phi_{i,\text{MT}}$ and the estimated OLS coefficients ϕ_i are identical in all panels, for all $i = 0, 1, ..., 5$. As also expected, the significance of the OLS coefficients according to the t-test are consistent with the respective significance of the Mishkin test's likelihood ratio statistics, which confirm that in our setting the models 26 and 35 yield equivalent inferences.

The coefficients in Panel A of Table 10 suggest that analysts on average overestimate the persistence of book value and correctly estimate the persistence of dividends. When we consider earnings components, however, analysts seem to underestimate the persistence of cash flows, normal accruals and abnormal accruals. In terms of persistence, the underestimation of earnings components seem to be counterintuitive, since previous analyses suggested that analysts are on average optimistic according to accounting information (see Figure 3). However, as pointed on Table 8, if a component have a negative impact on earnings, then an underestimation of the persistence of this component leads to positive forecast errors, which suggest optimism.

In terms of normal accruals and cash flows, as 88.64% and $13,48\%$ of normal accruals and cash flows are negative, respectively, the underestimation of these components suggests that the analysts' optimism according to the accounting components have been driven in part by normal accruals, and not by cash flows. In terms of abnormal accruals, however, further analyses are required, since almost 60% of abnormal accruals are positive.

Panel B and C of Table 10 present results of the Mishkin test and of the model 26 for portfolios composed by firms-year with positive and negative abnormal accruals, respectively. Note that, in terms of persistence, the results are qualitatively the same for all variables in both portfolios , except for abnormal accruals. The coefficient ϕ_2 of abnormal accruals on Panel B is not significant, while the coefficient ϕ_2 of abnormal accruals on Panel C is negative and significant at 5% significance level. These results suggest that analysts correctly estimate the persistence of positive abnormal accruals, but underestimate the persistence of negative abnormal accruals. In this case, the underestimation of abnormal accruals described on Panel A seem to be attributed to firms-year with negative abnormal accruals, which suggest that the analysts' optimism according to the accounting information have been driven also by negative abnormal accruals.

In summary, our results suggest that analysts are on average optimistic according to accounting information, and that book value, normal accruals, and negative abnormal accruals seem to be together the cause of this optimism. In the next subsection we provide further evidences about the contribution of abnormal accruals to the asymmetry in the positive tail of the distribution of analyst forecast errors according to the accounting components.

3.4.2 The Association between Extreme Abnormal Accruals and Analyst Forecast Errors

Past-accounting-basis forecast requires analysts to estimate future earnings basing on firm's past performances. Earnings with low quality are likely to provide noisier signals about firm's future earnings, leading to information asymmetry among managers, analysts, and the market. If past earnings provide less precise signals about firm's future earnings, analyst forecast errors related to the predictable time series component of earnings are likely to increase. Abarbanell and Lehavi (2003) present some evidences consistent with this prediction by identifying an empirical link between the recognition of negative unexpected accruals and an asymmetry in the positive tail of the distribution of analyst forecast errors. Bradshaw et al. (2001) also show that analyst forecasts do not incorporate the predictable future earnings declines associated with high accruals. Based on these evidences, we expect that the magnitude of the coefficients of the model 26 increase for high (negative) accruals firms.

As in Abarbanell and Lehavy (2003), we are using abnormal accruals to identify ex-post unexpected changes in accruals, in order to assess whether analyst forecast errors are related with these changes. If analysts do not account for the fact that firms may recognize high negative abnormal accruals, then we must have a link between positive analyst forecast errors and extreme negative abnormal accruals.

Table 11 present results for the model 26 when we consider dummies for firms-year with high abnormal accruals and negative abnormal accruals.

$$\begin{aligned}\epsilon_{t+1} &= \phi_0 + \phi_1 \text{CFO}_t + \phi_2 \text{NAC}_t + \phi_3 \text{ABNAC}_t + \phi_4 \text{Neg.ABNAC} + \phi_5 \text{High} + \phi_{56} \text{High.ABNAC}_t \\ &\quad + \phi_7 \text{High.Neg.ABNAC}_t + \phi_8 \text{BV}_t + \phi_9 \text{DIV}_t + u_{t+1}\end{aligned}$$

High is a dummy set as $1(0)$ for firms-year in the up (bottom) 30 percentile of the ranked absolute values of abnormal accruals. Neg is a dummy that indicates firms-year with negative abnormal accruals.

The coefficient ϕ_7 of high-negative abnormal accruals is negative and significant at 10% significance level, while the coefficients ϕ_3, ϕ_4, and ϕ_6 of abnormal accruals, high abnormal accruals, and negative abnormal accruals are not significant. Together, these results suggest that the analysts' underestimated persistence of abnormal accruals documented in the previous subsection seem to be attributed to firms-year with high negative abnormal accruals. This result corroborate with Abarbanell and Lehavy's (2003) findings, in which extreme negative unexpected abnormal accruals go hand in hand with observations that generate the tail asymmetry in the positive domain of forecast errors distribution.

Abarbanell and Lehavy (2003b) argue that one possible reason for the association between extreme negative abnormal accruals and extreme positive forecast errors is that firms may provide an "unforecasted earnings bath", recognizing large nondiscretionary or discretionary negative transitory operating and nonoperating items, at the same time as they recognize operating expenses larger than the operational expenses justified by the actual performance of the firm. In these situations, analysts also may have weaker incentives to release uninflated forecasts, since there are less cognitive obstacles that prevent them from revising their forecasts downward. These arguments, combined with the fact that analysts may have to work harder in their task to forecast extreme unusual accruals, could be possible explanations for why analysts do not correctly account for extreme negative abnormal accruals on their forecasts.

3.4.3 The Influence of Other Information on Inferences Concerning Analysts' Bias

Our measure of (expected) other information is based on the dimension of (expected) earnings that on average can not be explained by the accounting fundamentals. Similarly to Brian and Tiras (2007), we are using a methodology based on the residual of the regression of earnings (consensus analyst forecasts) on accounting fundamentals to identify earnings (expectations) that deviate from the persistence of accounting fundamentals in order to capture possible events that might configure other information.

Panel A of Table 12 present results of the model 29 controlling and not controlling for past accounting data. In order to identify the influence of positive and negative other information on analyst forecast errors, we included a dummy variable Neg set as 1 if the realized impact of other information on earnings was negative.

$$\widehat{V}_{t+1} = \beta_0 + \beta_1 \text{Neg} + \beta_2 V_{t+1} + \beta_3 \text{Neg}.V_{t+1} + \beta_4 \text{CFO}_t + \beta_5 \text{NAC}_t + \beta_6 \text{ABNAC}_t + \beta_7 \text{BV}_t + \beta_8 \text{DIV}_t + e_{t+1}$$

The coefficient β_2 is positive, significant, and statistically smaller than one at 1% significance level in both estimations. This result suggest that analysts underestimate positive other information, which in terms of good news are associated with negative forecast errors (pessimism[44]). This result could explain part of the inconsistence documented by Abarnanaell and Lehavy (2003) in the upside down U-shape that characterizes mean forecast errors over the range of unexpected accruals. According to Abarnanaell and Lehavy (2003), the apparent inconsistence in their results can be attributed to the fact that "if extreme positive unexpected accruals reflect misclassification in the case of firms that experience strong current performance, these would be the same cases in which analysts would tend to underreact to extreme current good news and issue forecasts that fall short of reported earnings", which is exactly the case in which firms experience large positive other information.

When we consider the estimated coefficient β_3 that account for the incremental effect of bad news over good news on expected other information, we obtain a negative and significant coefficient, which suggest that analysts underestimate even more negative other information over positive other information. Together, β_2 and β_3 suggest that analysts on average are pessimistic according to the impact of positive other information on earnings, but optimistic according to the impact of negative other information on earnings. At this point, negative other information could be a possible explanation for Abarbanaell and Lehavy's (2003) conclusion that "the middle asymmetry also contributes, albeit more subtly than the tail asymmetry, to producing OLS regression coefficients that are consistent with underreaction to bad news" (Abarbanaell and Lehavy, 2003).

Figures 5, 6 and 7 present a better overview of the influence of other information on analyst forecast errors distribution. The x-axis includes the percentiles of other information, while the right y-axis presents the value of each percentile. In Figures 5, 6 and 7, the left y-axis presents the mean of forecast errors, other-information forecast errors, and accounting forecast errors, respectively, as described by the solid lines, in intervals of 0.5% around each other information percentile.

According to Figure 5, smallest percentiles of other information are on average associated with larger positive forecast errors. When we decompose analyst forecast errors using our disaggregated approach,

[44] See Table 8 for further details about the interpretations of the impact of good and bad news on analyst forecast errors.

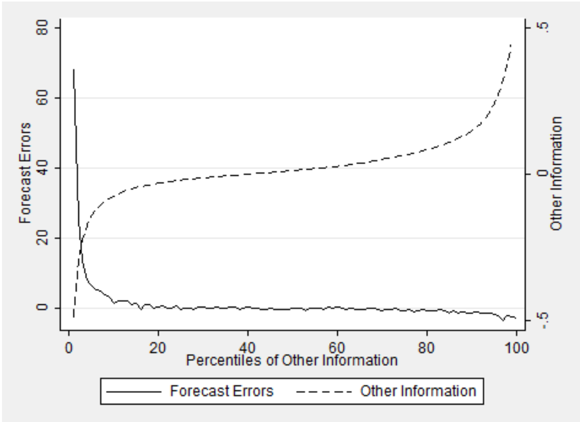


Figure 5: Mean of forecast errors, described by the the solid line, in intervals of 0.5% around each other information percentile.

Figure 6 shows that the means of forecast errors and other information forecast errors around each of these percentile look as the same. Untabulated mean comparison t-tests do not reject the null hypothesis of equal means at 1% or 5% significance level for the first 14 percentiles of other information. On the other hand, while largest percentiles of positive other information are on average associated with small negative forecast errors, Figure 6 shows that forecast errors are much larger when we consider only the forecast errors according to other information. Untabulated mean comparison t-tests reject the null hypothesis of equal means at 1% significance level for the last 25 percentiles of other information.

These analyses lead to two conclusions. First, analysts are neither optimistic nor pessimistic according to other information: it depends on the type, the sign, and the magnitude of the news. At this point, our results confirm prior evidences that analysts are optimistic according to negative other information and pessimistic according to positive other information. Second, Figures 5 and 6 suggest that even when analysts are right, they might be wrong. In other words, an accurate forecast can be done even when it is associated with large positive (negative) accounting errors and large negative (positive) other information errors.

3.4.4 Analyst Forecast Errors and Analyst Forecast Dispersion

Studies including Zhang (2006) find that greater information uncertainty predicts more positive[45] (negative) forecast errors and subsequent forecast revisions following good (bad) news, suggesting that information uncertainty delays the absorption of information into analyst forecasts. Once in uncertain economic environment firm's news are likely to provide noisier signals about future earnings, analyst forecast errors related to other information should increase when firms and analysts face uncertainty.

In order to identify the influence of forecast dispersion on analyst forecast errors according to other information, Panel B of Table 12 present results for the model 29 including a dummy variable High set as 1 for firms-year in the up 30 percentile of ranked analyst forecast dispersion, measured as the standard deviation of analysts' forecast scaled by the mean of analyst forecasts.

[45] Zhang (2006) measures forecast error as I/B/E/S actual earnings minus earnings forecast scaled by the prior year-end stock price.

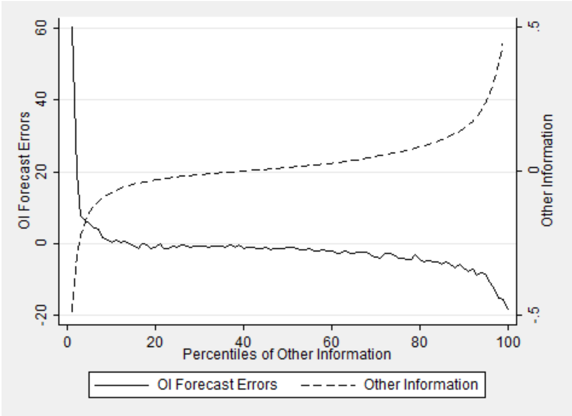


Figure 6: Mean of forecast errors according to other information, described by the solid line, in intervals of 0.5% around each other information percentile.

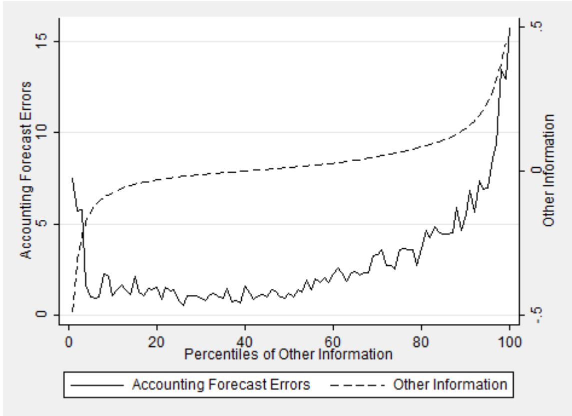


Figure 7: Mean of forecast errors according to the accounting components, described by the solid line, in intervals of 0.5% around each other information percentile.

$$\begin{aligned}\widehat{V}_{t+1} &= \beta_0 + \beta_1\text{Neg} + \beta_2\text{Neg.High} + \beta_3 V_{t+1} + \beta_4\text{Neg.}V_{t+1} + \beta_5\text{Neg.High.}V_{t+1} \\ &+\beta_6\text{CFO}_t + \beta_7\text{NAC}_t + \beta_8\text{ABNAC}_t + \beta_9\text{BV}_t + \beta_{10}\text{DIV}_t + e_{t+1}\end{aligned}$$

As in Panel A, the interpretation of the coefficients β_3, β_4, and β_5 suggest that analysts underreact to the impact of both positive and negative other information on earnings, but that the underreaction according to bad news seem to more severe for firms situated in poor information environments where analyst forecast dispersion is high. Untabulated results review that analysts also underreact more to good news when analyst forecast dispersion is high.

While more detailed analyses are beyond the scope of this paper, in summary, our results suggest that largest percentiles of positive (negative) other information are associated on average with large negative (positive) forecast errors, which corroborates with analysts being pessimistic (optimistic) according to extreme good (bad) news, and that these errors are more likely to be larger in poor information environments, where analyst forecast dispersion is high.

3.5 CONCLUSION

While the optimistic bias in forecast errors has been widely documented, a handful of other studies have failed to reject efficiency and unbiasedness in analyst forecasts after implementing approaches that minimize methodological flaws. One of the reasons for such empirical inconsistency is that in the literature too little is known about analysts' actual loss functions, and the usual methodologies thus leave unresolved the questions of what cause asymmetries in forecast errors distribution and to what extent analysts fully reflect public available information.

In this paper we implemented an approach that allow us to identify and test how accurate analysts are in processing information from two sources: accounting information and other information. Our methodology disaggregates analyst forecast errors into an error related with past accounting information and another error related with other information. In spite of some similarities among our descriptive statistics with the widely held beliefs among accounting and finance academics about analysts generally producing optimistic forecasts, analyses associated with the distribution of forecast errors of other information raises doubts about this conclusion.

In our analyses, far more extreme accounting (other information) forecast errors of greater magnitude are observed in the ex-post "optimistic" ("pessimistic") tail of the distribution than in the "pessimistic" ("optimistic") tail. These characteristics of the distributions of accounting and other information forecast errors suggest that analysts may have different behaviors in forecasting the persistence of accounting data and the impact of new information on earnings.

Our analyses lead to two conclusions. First, our results suggest that analysts are neither optimistic nor pessimistic: it depends on the type, the sign, and the magnitude of the information. In summary, our results review that analysts are on average optimistic according to the persistence of accounting information and that book value, normal accruals, and negative abnormal accruals are together the cause of this partial optimism. In the other information dimension, our results suggest that analysts seem to forecast positive other information not with optimism, but with pessimism, and that analysts are even more pessimistic according to good news in poor information environments, where analyst forecast dispersion is high. Second, our analyses present evidences that even when analysts are right, they might be wrong. In other words, accurate forecasts can be done even when it is associated with large positive accounting errors and large negative other information errors. In these cases, it seems that luck trumps skills.

Our study contributes to the analyst literature by documenting the association of analyst forecast errors with information beyond the accounting fundamentals. Our results present evidences that corroborate with analysts being optimistic, but also evidences that suggest pessimism. In particular, when financial accounting reports are less informative, as reflected by high abnormal accruals, our results suggest that analysts are more likely to forecast large positive errors. but also generate additional private information that reduces average forecast errors, This article also relates to prior studies focused on the use of analyst forecasts to infer characteristics of information environment (Barry and Jennings (1992), Abarbanell et al. (1995), etc). In this case, our results suggest that high information uncertainty predicts pessimistic forecasts according to good news.

With some modifications in the regression system commonly used in the Mishkin test, we also showed that our disaggregation approach leads similar conclusions to those obtained by the Mishkin test. Since control for other-information related factors and unusual-accruals related factors in the assessment of the relation between analyst forecast errors and analysts' interpretation of the persistence of accounting information and other information, respectively, is a hard task, our disaggregation methodology provides a parsimonious and less biased approach that specify the role of accounting fundamentals and other information on analysts' accuracy.

4 OTHER INFORMATION, ANALYSTS' FORECAST BIAS, AND STOCK PRICES: A THEORETICAL APPROACH

Abstract

Some researchers, based on the assumption that analysts' forecast contain information representing investors current expectation of future earnings, have used the regression residual of consensus analysts' forecast on accounting components to derive a proxy for other information. However, as several results suggest, analysts are generally optimistic and produce biased forecasts. Therefore, a proxy for other information derived directly from consensus analyst forecast is subject to analysts' bias, which can be even larger in poor information environments, where analyst forecast errors are also likely to be larger. In this paper we present an alternative approach that allow us to derive other information directly from stock prices, instead from consensus analyst forecast. Since price of equity, under market efficiency, fully reflects all public information, our derivation of other information intends to minimize the forecast bias present in the other information literature. Our analysis also reveals an implicit solution for the persistence parameters of the information dynamic, which satisfies Ohlson's (1995) assumptions.

4.1 INTRODUCTION

Edwards and Bell (1961) and Peasnell (1982) show that, by assuming only clean surplus relation, a firm's intrinsic value can be obtained by the sum of book value and the present value of expected future abnormal earnings (Residual Income Valuation Model - RIV). This inherent accounting appealing, however, is not sufficient to implement RIV, since expectations are unobservable and RIV is a function of expectations (Myers, 1999). Ohlson's (1995) contribution comes from the modeling of the Linear Information Dynamic[46] (LIM), which allows expected future earnings to be expressed as a function of contemporaneous accounting data, and other relevant information. The term other information, indeed, is theoretically designed to summarize value relevant events that have yet to have an impact in the financial statements, bearing upon future (abnormal) earnings independently of past (abnormal) earnings. Since these events impact earnings as opposed to the persistence of past earnings, there is a time-delay by the accounting measures to incorporate these value relevant information. This is one of the motivation for considering other information beyond earnings, book value, and dividends in valuation models.

Some authors including Dechow et al. (1999) and Brian and Tiras (2007), based on the argument that analysts' forecast of one-year-ahead earnings contain information representing investors' current expectation of future earnings, empirically implement RIV by deriving other information directly from consensus analysts' forecast. However, several results in the literature spanning finance, economics, and accounting raise concerns about the incentive misalignment between analysts and investors, and present evidences that analysts are generally optimistic and produce biased forecasts (Brown, Foster and Noreen (1985),

[46]The goal of the information dynamic is that it allows us to obtain a linear pricing solution in function of accounting information and other information, and only three accounting variables are required to summarize the accounting component. According to Rubinstein (2006), this approach of linking future information determining present value to current information can be viewed as a more sophisticated version of Willians' (1938) perpetual dividend growth model, and is an important contribution to subsequent empirical research by reorienting the way that accounting data is used to explain stock prices.

Stickel (1992), Abarbanell (1991), Stickel (1998), Das, Levine and Sivaramakrishnan (1998), Lin and McNichols (1998), Michaely and Womack (1999), Dechow, Hutton, and Sloan (2000), and Cowen, Groysberg and Healy (2006)).

The collective evidences from this literature suggest that analysts' forecast bias is motivated by competing interests in shaping analysts' outputs, as pressure from analysts' employers to issue favorable forecasts, the relationship between securities firms and their clients, analysts' dependence on managers for information, among others agency problems. Other studies including Zhang (2006) also argue that analysts' forecast errors are likely to be larger in environments with high information asymmetry. Together, these results suggest that using consensus analysts' forecast to estimate other information can cause an estimation bias of other information, which can be even larger in poor information environments.

In this paper we present an alternative approach that allow us to derive other information directly from stock prices instead from consensus analyst forecast. In our approach, only the variables described on Ohlson's (1995) model are required for the estimation procedure. Since price of equity, under Ohlson's (1995) assumptions and market efficiency, fully reflect all public information, our derivation of other information intends to mitigate the forecast bias present on methodologies that are directly affected by analysts' incentives to issue biased forecasts. Our analysis also reveals an implicit solution for the persistence parameters of the information dynamic, which satisfies Ohlson's (1995) assumptions.

This study relates to Kathryn et al. (2011), that document the association between returns and a characterization of other information based on the difference between changes in analysts' forecast and changes in realized accounting earnings. Kathryn et al. (2011) argue that other information captured in changes of forecasted earnings would allow the market to adjust for any non-permanent component in the current earnings. We point, however, that this characterization is sensitive to changes in analysts' incentives to issue biased forecasts, which makes unclear if returns are reflecting non-permanent components in the current earnings or adjusting for expectations of analysts' forecast error. By identifying the role of stock prices in estimating information beyond information contained in the financial statements and that affect future earnings, our study provides a natural setting that corroborate and extend prior literature.

Our study contributes to research on valuation by documenting the association between analyst forecast errors and biased estimations of other information. This article also relates to prior studies focused on the use of analysts' forecast to estimate other information and to infer characteristics of information environment (Brian and Tiras, 2007). At this point, given the concerns present in the literature about the significant incentive misalignment between analysts and investors, researchers should be more careful in using Ohlson's (1998, 2001) argument that analysts' forecast contain information representing investors' current expectation of future earnings to derive other information.

This article is organized as follows. In the next section we briefly introduce the Residual Income Valuation Model and the Linear Information Dynamic, in order to present the relations that support our estimation approach, and also to posit the estimation bias that exists in the current literature. In section 3 we derive other information directly from stock prices and show that this characterization of other information satisfies Ohlson's (1995) assumptions. Finally, section 4 presents a summary and conclusions.

4.2 OTHER INFORMATION AND ANALYSTS' FORECAST BIAS

Lo and Lys (2000) find that few studies have adequately evaluated the empirical validity of Ohlson's (1995) framework. One of these studies is Myers (1999), who explicitly attempts to incorporate order backlog as proxy for other information. However, even order backlog can not capture all impacts caused by news that change expectations of future earnings.

Other studies including Brian and Tiras (2007), based on the argument that analysts' forecast of one-year-ahead earnings contain information representing investors' current expectation of future earnings, empirically implement RIV by using the regression residual of consensus analysts' forecast on earnings and book value as proxy for other information. The results found by Bryan and Tiras (2007) validate Dechow et al.'s (1999) cross section findings, which generally support Ohlson's (1995) assumptions, and their further analysis present evidences that "in poor information environments where earnings quality is also poor, analysts are forced to focus less on accounting fundamentals and more on "other" relevant information beyond that reflected by the financial statements" (Bryan and Tiras, 2007).

Bryan and Tiras's (2007) results suggest that poor earnings quality forces analysts to weigh more heavily other value-relevant factors not reflected in earnings and book value. Intuitively, this evidence relies on the fact that "in poor information environments analysts are unlikely to invest additional resources to discern between noise and information in reported earnings" (Bryan and Tiras, 2007), since in this case the predictive ability of earnings is lower relative to good environments.

This approach in estimating other information using consensus analysts' forecast is based on the fact that consensus analysts' forecast can be used as proxy for expectations of future earnings. Theoretically, as Ohlson (1995) shows, it follows once the information dynamic, together with the clean surplus relation, allow us to restate expectations of future abnormal earnings $E_t[x^a_{t+1}] = wx^a_t + v_t$ (that are not directly observable in a practical perspective) as expectations of future earnings:

$$E_t[x_{t+1}] = wRx_t + (1-w)(R-1)b_t - w(R-1)d_t + v_t \tag{39}$$

However, as several results suggest, analysts are generally optimistic and forecast earnings with bias (Brown, Foster and Noreen (1985), Stickel (1992), Stickel (1998), Abarbanell (1991), Das, Levine and Sivaramakrishnan (1998), and Cowen, Groysberg and Healy (2006)). Other studies including Zhang (2006) also argue that analysts' forecast error are likely to be larger in environments with high information asymmetry. Together, these results suggest that using consensus analysts' forecast to estimate other information can cause an estimation bias of other information, which can be even larger in poor information environments.

In a recent study, So (2013) presents a new approach in predicting analysts forecast error that can be used to illustrate this estimation bias. So (2013) starts from the assumption that analysts not only have access to the predictable component of next-year earnings based on public signals $X_{1t}, X_{2t}, ..., X_{Mt}$, but also have private information and incentives to bias forecasts, which he denoted by $Z_{1t}, Z_{2t}, ..., Z_{Nt}$. In this case, analysts' forecast AF_t^{t+1} of one-year-ahead earnings could be written as

$$\mathsf{AF}_t^{t+1} = \widehat{\beta}_1 X_{1t} + \cdots + \widehat{\beta}_M X_{Mt} + \delta_1 Z_{1t} + \cdots + \delta Z_{Nt} + \eta_t$$

According to So (2013), this representation of analysts' forecast is motivated by a substantial literature documenting the role of competing interests in shaping analyst outputs, as pressure from analysts' employers to issue favorable forecasts, the relationship between securities firms and their clients, analysts' dependence on managers for information, among others agency problems. Based on these evidences, we argue that the residual of consensus analysts' forecast on public accounting information $X_{1t}, X_{2t}, \ldots, X_{Mt}$, which is given by

$$h_t^{t+1} = \mathsf{AF}_t^{t+1} - \widehat{\beta}_1 X_{1t} - \cdots - \widehat{\beta}_M X_{Mt} = \delta_1 Z_{1t} + \cdots + \delta Z_{Nt} + \eta_t$$

have also information about analysts' bias. Therefore, it cannot be used as proxy for other information without an appropriate data treatment, which empirically is hard to control for.

In a more recent study, Kathryn et al. (2011), following Ohlson (2001, Appendix 1), use an empirical model that relates returns to earnings, earnings change, and a characterization of other information based on the difference between changes in analysts' forecast and changes in realized accounting earnings. Kathryn et al. (2011) argue that other information captured in changes of forecasted earnings would allow the market to adjust for any non-permanent component in the current earnings. We point, however, that this characterization is sensitive to changes in analysts' incentives to issue biased forecasts, which makes unclear if returns are reflecting non-permanent components in the current earnings or adjusting for any expectation of analysts' forecast error. It follows because, by specifying the other information term as the difference between changes in analysts' forecast and changes in realized accounting earnings, other information would also capture changes in analysts' private information and changes in analysts' incentives to issue biased forecasts.

Without loss of generality, by considering the public signal X_{1t} in So's (2013) specification of analysts' forecast as realized accounting earnings, and β_1 representing analysts' expectations about earnings persistence, we have

$$\begin{array}{rl} \mathsf{AF}_t^{t+1} &= \beta_1 x_t + \beta_2 X_{2t} + \cdots + \beta_M X_{Mt} + \delta_1 Z_{1t} + \cdots + \delta Z_{Nt} + \eta_t \\ - \quad \mathsf{AF}_{t-1}^{t} &= \beta_1 x_{t-1} + \beta_2 X_{2t-1} + \cdots + \beta_M X_{Mt-1} + \delta_1 Z_{1t-1} + \cdots + \delta Z_{Nt-1} + \eta_{t-1} \\ \hline \Delta\mathsf{AF}_t^{t+1} &= \beta_1 \Delta x_t + \beta_2 \Delta X_{2t} + \cdots + \beta_M \Delta X_{Mt} + \delta_1 \Delta Z_1 + \cdots + \delta \Delta Z_N + \Delta\eta_t \end{array}$$

$$\Rightarrow \Delta\mathsf{AF}_t^{t+1} - \Delta x_{t+1} = \beta_1 x_t - \Delta x_{t+1} + \beta_2 \Delta X_{2t} + \cdots + \beta_M \Delta X_{Mt} + \delta_1 \Delta Z_1 + \cdots + \delta \Delta Z_N + \Delta\eta_t$$

The last equation shows that Kathryn et al.'s (2011) characterization of other information would purely reflect non-permanent components in the current earnings only if analysts' incentives to issue biased forecasts do not change in time, which seems an assumption that are not necessarily satisfied.

In the next section we present an alternative approach that allow us to derive other information directly from stock prices instead from consensus analysts' forecast. In our approach, only the variables described on Ohlson's (1995) model are required for the estimation procedure. Since price of equity, under Ohlson's (1995) assumptions and market efficiency, fully reflect all public information, our derivation of other information intends to mitigate the forecast bias present on methodologies that are directly affected by analysts' incentives and changes in analysts' incentives to issue biased forecasts.

4.2.1 RIV and the Linear Information Dynamic

The Residual Income Valuation Model is logically equivalent to the valuation model in which the firm's intrinsic value P_t is obtained by the sum of the expected present values of future dividends (Present Value Expected Dividends - PVED). Peasnell (1981) showed that, under clean surplus relation, market value can be written as book value plus the present value of future expected abnormal earnings. With an analogous implementation, let us consider the basic pricing equation

$$P_t = b_t + \sum_{\tau=1}^{\infty} E_t[b_{t+\tau} - Rb_{t+\tau-1} + d_{t+\tau}]R^{-\tau}$$

where $d_{t+\tau}$ symbolizes dividends received at the end of period $t+\tau$, $b_{t+\tau}$ represents book value, R is unity plus the cost os capital r, and E_t is the expected value operator. Assuming that in the accounting system all changes in book value b_t must bypass by the difference between earnings x_t and dividends (Clean Surplus Relation - CSR), and considering the abnormal earnings definition $x_t^a \equiv x_t - r.b_t$, we derive RIV (see Ohlson, 1995):

$$P_t = b_t + \sum_{\tau=1}^{\infty} E_t[x_{t+\tau}^a]R^{-\tau} \qquad (RIV) \tag{40}$$

The link between clean surplus relation and the present value of expected future dividends, however, is not sufficient to implement this valuation model, once expectations are unobservable and RIV is a function of expectations (Myers, 1999). In this case, an additional assumption that links observable information with expectation of future residual income is requested (Bernard, 1994). Ohlson's (1995) contribution comes from the modeling of the linear information dynamics, which allows expected future abnormal earnings to be expressed as a function of contemporaneous data. This dynamic hold as this second link and is based in two stochastic AR(1) process

$$x_{t+1}^a = wx_t^a + v_t + e_{1t+1}$$
$$v_{t+1} = \gamma v_t + e_{2t+1}$$

where w is the persistence of abnormal earnings, γ is the parameter that indicates the persistence of a shock (other information) v_t, and e_{it+1} is an unpredictable variable with zero mean, $i = 1, 2$. The parameters w and λ are restricted to be non-negative and less than one. This last condition assures that the unconditional means of both abnormal earnings and other information equal zero.

According to the information dynamic definition, other information must be not correlated with current (abnormal) earnings, since its predicted value $E_t[v_{t+1}]$ does not depend on (abnormal) earnings. The term v_t, indeed, is theoretically designed to summarize value relevant events that have yet to have an impact on the financial statements, bearing upon future (abnormal) earnings independently of current or past (abnormal) earnings. Since some relevant events impact future earnings as opposed to current earnings, there is a time-delay by the accounting measures to incorporate these value relevant information. This is one of the motivation for considering other information beyond earnings, book value, and dividends in valuation models.

The goal of the information dynamic is that it allows us to obtain a linear pricing solution in function of accounting information and other information, and only three accounting variables are required to summarize the accounting component. According to Rubinstein (2006), this approach of linking future information determining present value to current information can be viewed as a more sophisticated version of Willians' (1938) perpetual dividend growth model, and is an important contribution to subsequent empirical research by reorienting the way that accounting data is used to explain stock prices.

In order to obtain a linear pricing equation that does not depend directly on the expectation of future abnormal earnings and that incorporate the linear information dynamic, let us assume a linear solution $g_t = \alpha_1 x_t^a + \alpha_2 v_t$ for the infinite time series of the equation 40 that satisfies the risk neutrality assumption:

$$E_t[g_{t+1} + x_{t+1}^a] = Rg_t \tag{41}$$

In this case, by replacing the linear solution in equation 41, we get from the right side that

$$\begin{aligned} E_t[g_{t+1} + x_{t+1}^a] &= E_t[\alpha_1 x_{t+1}^a + \alpha_2 v_{t+1} + x_{t+1}^a] \\ &= E_t[x_{t+1}^a(1+\alpha_1) + \alpha_2 v_{t+1}] \\ &= (1+\alpha_1)[w x_t^a + v_t] + \alpha_2 \gamma v_t \\ &= (1+\alpha_1) w x_t^a + (1 + \alpha_1 + \alpha_2\gamma) v_t \end{aligned}$$

and from the left side that $Rg_t = R\alpha_1 x_t^a + R\alpha_2 v_t$. Equaling both sides, we obtain

$$(1+\alpha_1) w x_t^a + (1+\alpha_1+\alpha_2\gamma) v_t = R\alpha_1 x_t^a + R\alpha_2 v_t$$

and, equivalently, $\alpha_1 = \frac{w}{R-w}$ and $\alpha_2 = \frac{R}{(R-w)(R-\gamma)}$.

It shows that based on the linear information dynamic, if we assume a linear pricing solution for the Residual Income Valuation Model, then this linear valuation function has to be given by the following equation, as showed by Ohlson (1995):

$$P_t = b_t + \frac{w}{R-w} x_t^a + \frac{R}{(R-w)(R-\gamma)} v_t \tag{42}$$

This valuation function implies that market value equals book value adjusted for current abnormal earnings and for other information that modifies expectations of future earnings. If we do not consider other information in a valuation context, then it would indicate that current abnormal earnings alone determines the goodwill and it is also suffice in predicting one-year-ahead abnormal earnings, which seems an unreasonable assumption to assume.

Rewriting the valuation equation 42 by using CSR and the abnormal earnings definition, we obtain a linear pricing model based on current book value, earnings, dividends, and other information:

$$P_t = \phi_2 b_t + \phi_1 \left[\frac{x_t}{r}(1+r) - (d_t) \right] + \alpha_2 v_t \tag{43}$$

where $\phi_1 = \alpha_1(R-1)$ and $\phi_2 = 1 - \phi_1$. As ϕ_1 and ϕ_2 are positive parameters, the linear pricing equation 54 leads intuitively a positive association of the firm's intrinsic value with current earnings, book value, and other information, and also a negative association with the distributed dividends, as expected. In other words, an increase in current earnings and in the expectations of future earnings lead to an increase in the firm's value, and the distribution of dividends decreases the firm's value. Specifically, Ohlson (1995) shows that two closely related Modigliani and Miller properties are satisfied (MM 1958, 1961): dividends displace market value on a dollar-for-dollar basis (the irrelevance of dividends policy apply), and dividends paid today reduce future expected earnings.

4.2.2 Implications for LIM's Misspecifications

Lo and Lys (2000) argue that, despite of the relevance of other information for the valuation context, most part of the studies apply the Residual Income Valuation Model without considering the information dynamic, since RIV imposes data requirements that are impossible to meet in the actual empirical settings. The misspecification of the Linear Information Dynamic restrict RIV to more simplified models. In this subsection we briefly discuss each possible simplification, in order to enhance the importance of other information to the valuation context.

1. $w = 0$, ignoring other information:
   Models that ignores other information assume that expectations of future abnormal earnings are defined only by information contained in current abnormal earnings. In this specific case, by restricting the abnormal earnings persistence to equal 0, this model associates to abnormal earnings a character purely transitory. Together, these assumptions imply that expectations of future abnormal earnings are zero and, consequently, price equals book value. According to Dechow et al. (1999), this restricted version of Ohlson's model corresponds to valuation models in which accounting earnings are assumed to measure value creation (e.g., Easton and Harris, 1991).

2. $w = 1$, ignoring other information:
   In this case, by ignoring other information, expectations of future abnormal earnings are also assumed to be defined only by information contained in current abnormal earnings. By restricting the abnormal earnings persistence to equal 1, this model requires that abnormal earnings persist indefinitely. Together, these assumptions imply that expectations of future abnormal earnings and current abnormal earnings are equal. This result imply that price of equity equals book value plus current abnormal earnings capitalized in perpetuity. According to Dechow et al. (1999), this special case of Ohlson's model corresponds closely to the popular earnings capitalization valuation model in which earnings are assumed to follow a random walk and the future dividend payout ratio is assumed to be 100% (e.g., Kothari, 1992; Kothari and Zimmerman, 1995).

3. $0 < w < 1$, ignoring other information:
   In this case, by ignoring other information, expectations of future abnormal earnings are also assumed to be defined only by information contained in current abnormal earnings. By restricting the abnormal earnings persistence to be greater than 0 and less than 1, this model requires that abnormal earnings mean revert at their unconditional historical rate. In this case, expectations of future abnormal earnings equal current abnormal earnings multiplied by the persistence parameter w. Together, these results imply that price can be set as a linear function of book value and current abnormal earnings, and that the relative weight on book value (abnormal earnings) is decreasing (increasing) in the persistence parameter (Dechow et al., 1999).

4. $w = 0$ and $\gamma = 0$:
   In this case, other information are incorporated in the conditional expectation of future abnormal earnings, but both abnormal earnings and other information are assumed to have a character purely transitory. This result suggest that price equals book value plus the discounted value of expectations of

future abnormal earnings, and abnormal earnings have no implications for firm value beyond next period, once forecasted abnormal earnings are assumed to be purely transitory. (Dechow et al., 1999). Penman and Sougiannis (1998) apply this model considering a one period horizon and no terminal value.

5. $w = 1$ and $\gamma = 0$:
   In this case, abnormal earnings are expected to persist indefinitely, and other information are considered as transitory shocks. These assumptions imply that price equals expectations of next-year earnings capitalized in perpetuity. According to Dechow et al. (1999), variants of this model have long been popular in empirical applications of the dividend-discounting model, as in Whitbeck and Kisor (1963), Vander Weider and Carleton (1988), Frankel and Lee (1998), Lee et al. (1999), Penman and Sougiannis (1998), and Francis et al. (2000).

6. $w = 0$ and $\gamma = 1$:
   This model is identical to the model obtained in the last case. This result follows once $w = 0$ implies that expectation of one-year-ahead abnormal earnings equals other information, and $\gamma = 1$ imply that this expectation persist indefinitely (Ohlson, 1998).

7. $0 < w < 1$ and $\gamma = 0$:
   In this case, by assuming $\gamma = 0$, other information are not ignored, and then expectations of future abnormal earnings are assumed to be defined by the sum of information contained in current abnormal earnings and other information. The difference here is that other information is considered as purely transitory shocks. By restricting the abnormal earnings persistence to be greater than 0 and less than 1, this model requires that abnormal earnings mean revert at their unconditional historical rate. In this case, expectations of future abnormal earnings equal current abnormal earnings multiplied by the persistence parameter w plus other information. Together, these results imply that price can be set as a linear function of book value and expectations of future abnormal earnings. According to Dechow et al. (1999), while this model is appealing in that it combines expectations of future abnormal earnings with information in book value, it has received little attention in the empirical literature.

8. $w = 0$ and $0 < \gamma < 1$:
   Ohlson (1998) shows that the valuation function is symmetric in w and γ. This symmetry implies that this valuation model is identical to the last case in which $0 < w < 1$ and $\gamma = 0$. Intuitively, the only difference in this model is that expectations of abnormal earnings os the next period are entirely captured by other information, which imply that the persistence of next-year abnormal earnings equals γ.

4.3 USING STOCK PRICES TO ESTIMATE OTHER INFORMATION

Note that ϕ_1 from equation 54 can be rewrite as

$$\phi_1 = \frac{rw}{R - w} = \frac{rw}{R - w}\frac{R - \gamma}{R - \gamma} = \frac{rw(R - \gamma)}{\Delta} = k_1 + \frac{rwR}{\Delta}$$

where $\Delta = (R-w)(R-\gamma)$ and $k_1 = \frac{-rw\gamma}{\Delta}$. Then, by replacing ϕ_1 in equation 54, we obtain

$$P_t = k_1\left[\frac{R}{r}x_t - d_t\right] + \frac{rwR}{\Delta}\left[\frac{R}{r}x_t - d_t\right] + \phi_2 b_t + \alpha_2 v_t \tag{44}$$

As in equation 39, $E_t[x^a_{t+1}] = wx^a_t + v_t$ equals

$$E_t[x_{t+1}] = wRx_t + (1-w)(R-1)b_t - w(R-1)d_t + v_t$$

Therefore, by considering equation 39 in equation 44, we get

$$\alpha_2 v_t = \frac{R}{\Delta}\left[E_t[x_{t+1}] - wRx_t - (1-w)(R-1)b_t + w(R-1)d_t\right]$$

Follow that

$$P_t = k_1\left[\frac{R}{r}x_t - d_t\right] + \frac{R}{\Delta}E_t[x_{t+1}] + b_t\left[\phi_2 - (1-w)(R-1)\frac{R}{\Delta}\right] \tag{45}$$

Proposition 3.1 Equation 45 can be restate as

$$P_t = k_1\left[\frac{R}{r}x_t - d_t\right] + k_2 b_t + k_3\frac{E_t[x_{t+1}]}{r} \tag{46}$$

where $k_1 = \frac{-rw\gamma}{\Delta}$, $k_2 = \frac{R}{\Delta}(1-\gamma)(1-w)$, $k_3 = \frac{rR}{\Delta}$ and $k_1 + k_2 + k_3 = 1$.

In fact, for $k_2 = \frac{R}{\Delta}(1-\gamma)(1-w)$, we have

$$\begin{aligned} k_2 &= \tfrac{R}{\Delta}(-\gamma - w - rw + w\gamma + 1 + wR - w) \\ &= \tfrac{1}{\Delta}(-R\gamma - wR + w\gamma - rwR + (R-1)w\gamma + R + wR^2 - Rw) \\ &= \tfrac{1}{\Delta}(-R\gamma - wR + w\gamma - rwR + rw\gamma + R + wR^2 - Rw) \\ &= \tfrac{1}{\Delta}[(R-w)(R-\gamma) - rw(R-\gamma) - R(1-w)(R-1)] \\ &= \phi_2 - \tfrac{R(1-w)(R-1)}{\Delta} \end{aligned}$$

Follow that

$$\begin{aligned} k_2 y_t &= \left[\phi_2 - \tfrac{R(1-w)(R-1)}{\Delta}\right] b_t \\ &= x_t\left[\tfrac{R^2 w}{\Delta} - \tfrac{R^2 w}{\Delta}\right] + d_t\left[\tfrac{-rwR}{\Delta} + \tfrac{(R-1)wR}{\Delta}\right] + \left[\phi_2 - \tfrac{R(1-w)(R-1)}{\Delta}\right] y_t \\ &= \tfrac{rwR}{\Delta}\left[\tfrac{R}{r}x_t - d_t\right] + \left[\phi_2 - \tfrac{R(1-w)(R-1)}{\Delta}\right] b_t + \tfrac{rwR}{\Delta}\left[-\tfrac{R}{r}x_t + d_t\right] \end{aligned}$$

Adding $k_1\left[\frac{R}{r}x_t - d_t\right] + \frac{R}{\Delta}E_t[x_{t+1}]$ in both sides we obtain the equivalence between 45 and 46, as we wanted to prove.

Equation 45 suggest that market value is a function of current earnings, dividends, and book value, adjusted for expectations of future earnings. The parameters k_1, k_2, and k_3 are related to the persistence of abnormal earnings and other information, and incorporate the effect of the linear information dynamic on RIV. As these coefficients are functions of the persistence parameters, we can write w or γ as functions of k_1, k_2 and k_3. After some maths, we get from k_1, k_2 and k_3, respectively, that

$$\gamma = \frac{k_1 R(R-w)}{[k_1(R-w) - rw]} \tag{47}$$

$$\gamma = \frac{R[1 - w - k_2(R - w)]}{R(1 - w) - k_2(R - w)} \quad (48)$$

$$\gamma = \frac{R[k_3(R - w) - r]}{k_3(R - w)} \quad (49)$$

Equaling the equations 47 and 48, and 47 and 49 we obtain exactly the same equation, that follows:

$$k_3 w^2 + w(r + k_1 - k_3 R) - k_1 R = 0 \quad (50)$$

In this case, the parameters of the linear information dynamic are well-defined only if the regularity conditions $R1$ and $R2$ below are satisfied:

$$(r + k_1 - k_3 R)^2 = -4k_3 R k_1 \quad (R1)$$

$$k_3 - k_1 \geq r(1 - k_3) \quad (R2)$$

Assuming $R1$ and $R2$, we find

$$w = \frac{k_3 R - r - k_1}{2k_3} \quad (51)$$

Finally, substituting 51 in 47 leads to

$$\gamma = \frac{k_1 R(R - w)}{[k_1(R - w) - rw]} \quad (52)$$

Given the theoretical relation $k_1 + k_2 + k_3 = 1$, without loss of generality, the persistence parameter w in equation 51 could be restated in function of k_1 and k_2 instead of k_1 and k_3, as follows:

$$w = \frac{[1 - k_1 - k_2]R - r - k_1}{2[1 - k_1 - k_2]} \quad (53)$$

Proposition 3.2 Considering PVED, *clean surplus relation*, the Linear Information Dynamic

$$\begin{aligned} x^a_{t+1} &= w x^a_t + v_t + e_{1t+1} \\ v_{t+1} &= \qquad \gamma v_t + e_{2t+1} \end{aligned}$$

and the regularity conditions $R1$ and $R2$, we have that the implicit solutions for the persistence parameters w and γ given as in equations 51 and 52, respectively, satisfy Ohlson's (1995) assumptions.

In fact, as $k_3 + k_1 < 1$, we have

$$\begin{aligned} -r(k_3 + k_1) + r > 0 \quad &\Rightarrow k_3(1 - R) + k_1(1 - R) + r > 0 \\ &\Rightarrow Rk_1 < k_3 + r + k_1 - k_3 R \\ &\Rightarrow (r + k_1 - k_3 R) + 4k_3 R k_1 < [2k_3 + (r + k_1 - k_3 R)]^2 \\ &\Rightarrow k_3 R - r - k_1 + \sqrt{(r + k_1 - k_3 R)^2 + 4k_3 R k_1} < 2k_3 \\ &\Rightarrow w < 1 \end{aligned}$$

On the other hand, as $\gamma = \frac{k_1 R(R-w)}{[k_1(R-w)-rw]}$ and $k_1 < 0$, we obtain $\gamma > 0$. Supposing by contradiction that $\gamma > 1$, we should have

$$\begin{aligned}
\tfrac{k_1 R(R-w)}{[k_1(R-w)-rw]} > 1 \quad & \Rightarrow k_1 R(R-w) < k_1(R-w) - rw \\
& \Rightarrow k_1(R-w)(R-1) < -rw \\
& \Rightarrow w - wk_1 + k_1 R < 0 \\
& \Rightarrow k_1(R-w) > w
\end{aligned}$$

which is an absurd. Therefore, both w and γ are greater than 0 and less than 1, which satisfy Ohlson's (1995) assumptions.

4.3.1 Estimating Other Information

In the last subsection we obtained implicit solutions for the parameters of the Linear Information Dynamic directly from the linear pricing solution proposed by Ohlson (1995). We showed that these solutions, under the regularity conditions, satisfy Ohlson's (1995) assumptions. In our approach, only price of equity, earnings, book value, and dividends are required to estimate the persistence parameters $\widehat{w}$ and $\widehat{\gamma}$. In approaches that consider other information as a component of consensus analysts' forecast, it is difficult to distinguish between analysts' incentive to bias and other information. In our approach, however, other information does not depend directly on expectations of future earnings, but on how these expectations have affected stock prices.

In our approach, based on equations 52 and 53, the estimated persistence parameters $\widehat{\gamma}$ and $\widehat{w}$ are functions of the discount factor R and of the estimated coefficients β_1 and β_2 of the regression

$$P_t = \beta_0 + \beta_1 \left[\frac{R}{r} x_t - d_t\right] + \beta_2 y_t + e_t$$

where $E[\beta_1] = k_1 = \frac{-r\widehat{w}\widehat{\gamma}}{\widehat{\Delta}}$, $E[\beta_2] = k_2 = \frac{R}{\widehat{\Delta}}(1-\widehat{\gamma})(1-w)$, and $\widehat{\Delta} = (R-\widehat{w})(R-\widehat{\gamma})$, as follows:

$$\widehat{w} = \frac{[1-\widehat{\beta}_1-\widehat{\beta}_2]R - r - \widehat{\beta}_1}{2[1-\widehat{\beta}_1-\widehat{\beta}_2]}$$

$$\widehat{\gamma} = \frac{\widehat{\beta}_1 R(R-\widehat{w})}{[\widehat{\beta}_1(R-\widehat{w}) - r\widehat{w}]}$$

The goal of the implicit solutions for the persistence parameters of the information dynamics is that it allow us to use equation 54 to estimate other information directly from stock prices, since v_t can be written as

$$v_t = \frac{1}{\alpha_2}\left[P_t - \phi_2 b_t - \phi_1\left(\frac{x_t}{r}(1+r) - (d_t)\right)\right] \tag{54}$$

where ϕ_1, ϕ_2 and α_2 are functions of w and γ. In our approach, other information is not derived as a component of expectations of future earnings, but depends on the impact of these expectations on stock prices.

It is important to note that our approach in estimating other information preserves the properties of the Residual Income Valuation Model. As Ohlson (1995) showed, two closely related Modigliani and

Miller properties are satisfied (MM 1958, 1961): dividends displace market value on a dollar-for-dollar basis (the irrelevance of dividends policy apply), and dividends paid today reduce future expected earnings. These results, together with the Clean Surplus Relation, corroborate with the orthogonality between other information and past accounting information, in special dividends paid at period t. It follows because from CSR, as in Ohlson (1995), we have

$$\begin{array}{ccccccc} \frac{\partial b_t}{\partial d_t} & = & \frac{\partial b_{t-1}}{\partial d_t} & + & \frac{\partial x_t}{\partial d_t} & - & \frac{\partial d_t}{\partial d_t} \\ -1 & & 0 & & 0 & & 1 \end{array}$$

Then, from equation 54, the partial derivative of other information on dividends d_t can be set as

$$\begin{aligned} \frac{\partial v_t}{\partial d_t} &= \frac{1}{\alpha_2}\left[\frac{\partial P_t}{\partial d_t} - \phi_2 \frac{\partial b_t}{\partial d_t} - \phi_1 \left(\frac{(1+r)}{r}\frac{\partial x_t}{\partial d_t} - \frac{\partial d_t}{\partial d_t}\right)\right] \\ &= \frac{1}{\alpha_2}(-1 + \phi_2 + \phi_1) \end{aligned}$$

As $\phi_2 = 1 - \phi_1$, we have $\frac{\partial v_t}{\partial d_t} = 0$, as expected.

Ohlson (1995) explain this result by arguing that "this condition naturally make sense if one think v_t as capturing all non-accounting information in the prediction of future abnormal earnings." Although v_t is designed to represent broader issues, the requirement $\frac{\partial v_t}{\partial d_t} = 0$ is a model simplification that avoid irrelevant specification issues.

4.4 CONCLUSION

Ohlson (1995) proposes a theoretical model that relates the Residual Income Valuation Model with a Linear Information Dynamic that allows expected future earnings to be expressed as a function of contemporaneous accounting data and other relevant information. The goal of Ohlson's (1995) Information Dynamic is that it allows price to be set as a linear valuation function that depends of accounting information and other information, and only three accounting variables are required to summarize the accounting component. As Rubinstein (2006) posits, this approach of linking future information determining present value to current information can be viewed as a more sophisticated version of Willians' (1938) perpetual dividend growth model, and is an important contribution to subsequent empirical research by reorienting the way that accounting data is used to explain stock prices.

Some studies, however, have applied the Residual Income Valuation Model without considering other information. As discussed in this paper, this omission can cause misspecifications in terms of valuation and also requires assumptions that cannot capture changes in expectations of future earnings. On the other hand, other studies have used consensus analyst forecast to derive other information. Brian and Tiras (2007), for example, based on Ohlson's (2001, 112-113) argument that analysts' forecast of one-year-ahead earnings contain information representing investor's current expectation of future earnings, empirically implement RIV by using the regression residual of consensus analysts' forecast on earnings and book value as proxy for other information. This approach is similar to the approach used by Ohlson and Shroff (1992) for identifying new information in reported earnings and by Manry et al. (2003), who identify new information in reported quarterly earnings.

However, several results in the literature spanning finance, economics, and accounting raise concerns about the incentive misalignment between analysts and investors, and present evidences that analysts are optimistic and produce biased forecasts. Other studies including Zhang (2006) also argue that analysts' forecast error are likely to be larger in environments with high information asymmetry. Together, these results suggest that use consensus analyst forecast to estimate other information can cause an estimation bias. Using So's (2013) specification of analysts' forecast, we theoretically documented the association between analyst forecast errors and biased estimations of other information.

In this paper we also presented an alternative approach that uses stock prices instead of analysts' forecast to derive other information. Our analyses reveals an implicit solution for the persistence parameters of the information dynamic, which satisfies Ohlson's (1995) assumptions and preserves internal consistency. Since price of equity, under Ohlson's (1995) assumptions and market efficiency, fully reflect all public information, our approach intended to mitigate the forecast bias present on the estimation of other information in the current literature.

Our study contributes to research on valuation by theoretically documenting the association between analyst forecast errors and biased estimations of other information. This article also relates to prior studies focused on the use of analysts' forecasts to estimate other information and infer characteristics of information environment (Brian and Tiras, 2007). At this point, given the concerns present in the literature about the significant incentive misalignment between analysts and investors, researchers should be more careful in using Ohlson's (2001, 112-113) argument that analysts' forecast contain information representing investors' current expectation of future earnings.

This paper yields several issues for future researches. First, as Brian and Tiras's (2007) results suggest, in poor information environments analysts are forced to focus less on accounting fundamentals and more on "other" relevant information beyond that reflected by the financial statements. This relation, however, could have been affected by an endogenous problem present in their analyses involving the other information estimation bias and their proxy for environment quality (analyst dispersion). In this case, it is still not clear the rule of other information in predicting future earnings when the information asymmetry is high. Second, as Bradshaw, Sloan, and Richardson (2001) document, analysts' forecast do not incorporate earnings declines associated with high-accrual firms. In this case, it is still not clear the rule of other information in predicting future earnings when information contained in the financial statements have a low quality. While empirical analyses are beyond of the scope of this paper, our theoretical approach could be used to explain the rule of other information on earnings predictability under high information asymmetry and low earnings quality. In these cases, other information could be estimated before the earnings announcement in an ex-ante analysis, and only stock prices and past accounting data would be required.

5 CONCLUSION

This dissertation addressed three issues based on other information: first, we implemented market efficiency tests in order to verify whether stock prices fully reflect the impact of other information contained in analysts' forecast according to its association with one-year-ahead earnings; second, we developed an analyst forecast error disaggregation approach in order to verify whether analysts fully reflect other information according to its association with realized earnings; and finally, we documented a bias on the estimation procedures of other information commonly used in the current literature and suggested a new proxy for other information that is derived directly from stock prices instead from analysts' forecast.

In the analyses of the first research question, we attributed any market mispricing of other information to the market's failure to correctly weigh this information according to its impact on one-year-ahead earnings. In order to justify this attribution, we presented a theoretical analysis of the relation among one-year-ahead earnings news, a hypothetical other information market weight function, the market expectation of the impact of other information, and the realized impact of this information as reflected in its association with one-year-ahead earnings. In particular, we claimed that the market reacts for both negative and positive other information, but gives more weight for bad news than for good news, which is consistent with the loss-aversion principle, as showed by Kahneman and Tversky (1979).

Based on the equivalence between the Mishkin test and a LS model in large samples, in order to make empirical inferences about the marginal variation of the market's mispricing of other information, and also to test if this market's mispricing holds as the magnitude of the impact of good and bad news on one-year-ahead earnings increase, we also considered a non linear model that contain a quadratic term and a dummy for negative values of other information. We also included in this non linear model quadratic terms and dummies for negative values of earnings components, in order to verify if the accruals anomaly documented by Xie (2001) increase or decrease with the magnitude of normal and abnormal accruals.

Empirical analyses confirmed our predictions. As expected, other information are positively correlated with current returns and size-adjusted abnormal returns, and also with next year earnings, but not correlated with past earnings. Our analyses also review that good (bad) news on average increase (reduce) the firm's market value. This result is consistent with the linear pricing solution proposed by Ohlson (1995). The results of the Mishkin test suggest that the market acts as if it on average underprices the impact of good news and overprices the impact of bad news on future earnings, which is consistent with our assumption that the market gives on average more weight for bad news than for good news. The non linear analysis, however, reviews that the market not only underprices (overprices) the impact of positive (negative) other information, but tends also to overprice the impact of positive other information when the expected impact of this information on future earnings is sufficiently large.

Since size-adjusted abnormal returns are positively correlated with other information, on average firms with negative other information experience negative returns, and firms with positive other information experience positive returns. The hedge portfolio test shows that a trading strategy taking a long position in firms with past negative other information, and a short position in firms with past positive other information yields positive abnormal stock returns in the subsequent year. This result provides evidences that the market overprices extreme other information contained in analysts' forecast.

Our results also suggest that the overpricing of extreme news seems to be more severe for bad news over good news, and is higher when analysts highlight and agree about the impact of such news on future earnings. These evidences extend Brian and Tiras's (2007) results by suggesting that stock prices not only reflect information other than earnings, book value, and dividends provided by analysts, but also that the market overprices this information, specially when the expected impact of these news on future earnins are sufficiently large and analysts agree about it.

In summary, in the first chapter, we extend the current literature by presenting evidences that the market does not correctly price the impact of other information contained in analysts' forecast, and also fails to price appropriately the impact of bad and good news on future earnings. Moreover, we provide evidences that the market overprices other information leading to arbitrage, which is larger when the expected impact of these news on future earnings are sufficiently large and when analysts agree about it.

In this analyses of the second issue (chapter 3), we implemented an approach that allow us to identify and test how accurate analysts are in processing information from two sources: accounting information and other information. Our methodology disaggregates analyst forecast errors into an error related with past accounting information and another error related with other information. In spite of some similarities among our descriptive statistics with the widely held beliefs among accounting and finance academics about analysts generally producing optimistic forecasts, analyses associated with the distribution of forecast errors of other information raises doubts about this conclusion.

In our analyses, far more extreme accounting (other information) forecast errors of greater magnitude are observed in the ex-post "optimistic" ("pessimistic") tail of the distribution than in the "pessimistic" ("optimistic") tail. These characteristics of the distributions of accounting and other information forecast errors suggest that analysts may have different behaviors in forecasting the persistence of accounting data and the impact of new information on earnings.

Our analyses lead to two conclusions. First, our results suggest that analysts are neither optimistic nor pessimistic: it depends on the type, the sign, and the magnitude of the information. In summary, our results review that analysts are on average optimistic according to the persistence of accounting information and that book value, normal accruals, and negative abnormal accruals are together the cause of this partial optimism. In the other information dimension, our results suggest that analysts seem to forecast positive other information not with optimism, but with pessimism, and that analysts are even more pessimistic according to good news in poor information environments, where analyst forecast dispersion is high. Second, our analyses present evidences that even when analysts are right, they might be wrong. In other words, accurate forecasts can be done even when it is associated with large positive accounting errors and large negative other information errors. In these cases, it seems that luck trumps skills.

At this point, our study contributes to the analyst literature by documenting the association of analyst forecast errors with information beyond the accounting fundamentals. Our results present evidences that corroborate with analysts being optimistic, but also evidences that suggest pessimism. In particular, when financial accounting reports are less informative, as reflected by high abnormal accruals, our results suggest that analysts are more likely to forecast large positive errors. but also generate additional private information that reduces average forecast errors, Our findings also relate to prior studies focused on the use of analyst forecasts to infer characteristics of information environment (Barry and Jennings (1992), Abarbanell et al.

(1995), etc). In this case, our results suggest that high information uncertainty predicts pessimistic forecasts according to good news.

With some modifications in the regression system commonly used in the Mishkin test, we also showed that our disaggregation approach leads similar conclusions to those obtained by the Mishkin test. Since control for other-information related factors and unusual-accruals related factors in the assessment of the relation between analyst forecast errors and analysts' interpretation of the persistence of accounting information and other information, respectively, is a hard task, our disaggregation methodology provides a parsimonious and less biased approach that specify the role of accounting fundamentals and other information on analysts' accuracy.

In chapter 4, we addressed our last issue. Several results in the literature spanning finance, economics, and accounting raise concerns about the incentive misalignment between analysts and investors, and present evidences that analysts are optimistic and produce biased forecasts. Other studies including Zhang (2006) also argue that analysts' forecast error are likely to be larger in environments with high information asymmetry. Together, these results suggest that use consensus analyst forecast to estimate other information can cause an estimation bias. Using So's (2013) specification of analysts' forecast, we theoretically documented the association between analyst forecast errors and biased estimations of other information.

In order to mitigate the forecast bias of the other information estimation procedures present in the current, we presented an alternative approach that uses stock prices instead of analysts' forecast to derive other information. Our analyses reveals an implicit solution for the persistence parameters of the information dynamic, which satisfies Ohlson's (1995) assumptions and preserves internal consistency. An advantage of our approach is that only variables present on the Ohlson's (1995) model are required and no further assumption is necessary.

At this point, our study contributes to research on valuation by theoretically documenting the association between analyst forecast errors and biased estimations of other information. Our study also relates to prior studies focused on the use of analysts' forecasts to estimate other information and infer characteristics of information environment (Brian and Tiras, 2007). At this point, given the concerns present in the literature about the significant incentive misalignment between analysts and investors, researchers should be more careful in using the argument that analysts' forecast contain information representing investors' current expectation of future earnings.

According to the equivalence between the Mishkin test and OLS, although OLS is an easier method to implement and allows more straightforward comparisons among accounting researches, this method has a disadvantage according to it interpretation, since it depends on the signal and significance of the parameter β that cannot be estimated in the OLS model. If accounting researchers decide to use OLS, we suggest them to state more explicitly the theoretical reasons that support the signal and the significance of the coefficient β in their research settings or, alternatively, consider using both methods or only the Mishkin test.

Together, our study yields several issues for future researches. First, as Brian and Tiras's (2007) results suggest, in poor information environments analysts are forced to focus less on accounting fundamentals and more on "other" relevant information beyond that reflected by the financial statements. This relation, however, could have been affected by an endogenous problem present in their analyses involving the other information estimation bias and their proxy for environment quality (analyst dispersion). In this case, it is still not clear the rule of other information in predicting future earnings when the information asymmetry is high. Second, as Bradshaw, Sloan, and Richardson (2001) document, analysts' forecast do not incorporate earnings declines associated with high-accrual firms. In this case, it is still not clear the rule of other information in predicting future earnings when information contained in the financial statements have a low quality. Third, future researches could examine the relation between abnormal accruals and other information in a conservative accounting system, also investigating when the overpricing of abnormal accruals are due to discretionary managerial behavior or unusual economic circumstances. Finally, although OLS allows us to implement extra analyses that are difficult to be implemented by using the Mishkin test, it is still difficult to completely rule out unknown risk factors that could affect our results, specially in environments with high information asymmetry and low earnings quality. Restructure the Ohlson's (1995) information dynamic in order to adjust for heterogeneous belief, information asymmetry, and low earnings quality is still an open research question.

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Table 5: **Mean of Other Information, Earnings Components, Market Value, and Size-Adjusted Abnormal Returns for each Other-Information Decile Portfolio formed Annually by Assigning Firms to Decile Based on the Magnitude of Ranked Other Information**[a]

Decile	$\widehat{V}_t$	CFO$_t$	NAC$_t$	ABNAC$_t$	SIZE$_{t+1}$	ABRET$_{t+2}$	ABRET$_{t+3}$
Lowest$(-)$	-0.0998***	0.0688***	-0.0697***	0.0204***	2326.951	20.38***	16.50***
2	-0.0294***	0.1126***	-0.0574***	0.0083***	3867.12	14.68***	13.98***
3	-0.0164***	0.1120***	-0.0549***	0.0069***	3547.548	11.45***	9.97***
4	-0.0088***	0.1037***	-0.0527***	0.0023*	4410.83	7.73***	5.90***
5	-0.0032***	0.1028***	-0.0548***	-0.0004	3764.305	5.17***	4.99***
6	0.0018***	0.1030***	-0.0559***	0.0001	4704.567	2.78***	4.01***
7	0.0075***	0.1066***	-0.0533***	-0.0031***	5230.663	0.87	2.98***
8	0.0154***	0.1121***	-0.0550***	-0.0041***	5942.993	-0.84	0.98
9	0.0296***	0.1192***	-0.0579***	-0.0062***	6336.956	-3.66***	-0.68
Highest$(+)$	0.1033***	0.0930***	-0.0690***	-0.0163***	6145.183	-5.42***	-0.74
Mean	0.0000	0.1034	-0.0580	0.0008	4627.923	5.31	5.80
N. Obs.	41243	41243	41243	41243	41243	39221	37104
Hedge[b]						24.16***	15.79***

[a] Decile portfolios are formed annually by ranking firms according to other information and assigning firms to decile based on the magnitude of ranked other information. Variables definitions are present in Table 1. $*$, $**$, and $***$ represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

[b] Although the last two columns of this Table present the means of size-adjusted abnormal returns for each other-information decile portfolio by considering all firms-year of our sample, we applied the hedge portfolio test on December 31st fiscal-year-end firms-year once the hedge portfolio has to be assigned and maintained fixed during the buy-and-hold period.

Table 6: **Two-Years-Ahead Earnings Model using Other Information based on Realized Earnings**

Panel Data Analysis[a] Considering the First and the Alternative Estimation Procedure[b]

		First Estimation Procedure			***Alt. Estimation Procedure***		
Variable	Parameter	Estimate[c]	Std. Error	$P > \|t\|$	Estimate	Std. Error	$P > \|t\|$
CFO_{t+1}	β_1	0.2618***	0.0052	0.000	0.2483***	0.0125	0.000
NAC_{t+1}	β_2	0.1729***	0.0070	0.000	0.1681***	0.0171	0.000
ABNAC_{t+1}	β_3	0.0790***	0.0060	0.000	0.0347***	0.0126	0.006
CFO_t	β_4	0.0537***	0.0036	0.000	0.0380***	0.0103	0.000
NAC_t	β_5	0.0701***	0.0054	0.000	0.0213	0.0154	0.166
ABNAC_t	β_6	0.0270***	0.0047	0.000	-0.0132	0.0098	0.177
V_t	β_7	0.1272***	0.0126	0.000	0.2349***	0.0244	0.000
$D.\text{V}_t$	β_8	-0.0160	0.0184	0.384	-0.1745***	0.0314	0.000
	β_0	0.0279***	0.0008	0.000	0.0250***	0.0018	0.000
Number of Obs.		39,495			16,640		
F Statistic		1129.64			194.61		
Adj R-squared		19.59%			9.76%		

[a] This table presents results for the estimation of the model described bellow:

$$\text{EARN}_{t+2} = \beta_0 + \beta_1\text{CFO}_{t+1} + \beta_2\text{NAC}_{t+1} + \beta_3\text{ABNAC}_{t+1} + \beta_4\text{CFO}_t + \beta_5\text{NAC}_t + \beta_6\text{ABNAC}_t + \beta_7\widehat{V}_t + \beta_8 D.\widehat{V}_t + \epsilon_{t+1}$$

Earnings components definitions are present in Table 1. We estimated the realized impact of other information on earnings of $t+1$ by replacing consensus analysts' forecast for realized earnings of $t+1$ in equation 14 for both estimation procedures. D is a dummy set as 1 if V_t is negative, and 0, otherwise.

[b] Our sample is identified by merging firms listed on Compustat and I/B/E/S over 1983 to 2012. Monthly returns data were obtained on CRSP database. In the end, we obtained a sample size of $41,243$ observations over our 30-year sample period, in which $39,945$ firms-year have information about earnings of $t+2$. When we considered our alternative other information estimation procedure, our sample size reduced to $19,971$ firms-year observations, in which $16,640$ have information about earnings of $t+2$

[c] $*$, $**$, and $***$ represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

Table 7: **Mean of Size-Adjusted Abnormal Returns for Portfolios based on Other Information and Analysts' Forecast Dispersion**[a]

Panel A: Mean of Size-Adjusted Abnormal Returns Considering the First Estimation Procedure

Decile[b]	1	2	3	4	5	6	7	8	9	10
1	**37.60**	10.69**	16.29*	**16.33**	**23.22**	22.98**	**14.20**	11.64**	12.47**	**25.15**
2	**26.37**	6.56**	**8.55**	5.82**	10.64**	**13.71**	**14.38**	**15.36**	**25.73**	**14.52**
3	**21.55**	4.38**	5.89**	**8.49**	8.35**	6.51**	3.95*	**12.52**	16.49**	6.27
4	**15.95**	**7.78**	**5.15**	**7.28**	1.17	3.37	4.17	**9.84**	**9.89**	8.74*
5	**13.68**	0.35*	2.85	1.46	2.15	3.77*	1.88	2.87	9.76*	1.99
6	**11.55**	-0.14	-3.06	1.28	-2.83	2.90	1.97	4.19	7.06	4.40
7	2.08	-2.91*	-0.68	-2.82	-3.71*	2.52	1.67	5.09*	2.42	-2.16
8	0.91	-1.21	-2.17	-4.13*	0.30	3.31	-6.47**	1.08	1.18	5.31
9	0.22	-6.48**	-5.33**	-2.52	-7.38**	0.26	-0.93	-5.44*	1.01	4.47
10	8.37	**-12.11**	**-13.66**	**-13.46**	-2.62	-4.04	-1.22	2.49	-2.04	6.97
Mean(C_2)[c]	**15.94**	-0.74	-0.19	0.57	**1.54**	**4.73**	**3.28**	**6.41**	**9.69**	**10.92**
Mean(R_2)	**20.65**	**15.97**	**10.24**	**7.40**	**4.06**	**2.52**	0.05	-0.52	**-2.77**	-3.51**
Mean(R_3)	**16.52**	**11.91**	**9.51**	**4.98**	**4.95**	**5.47**	**3.59**	2.54**	0.17	0.73

Panel B: Mean of Size-Adjusted Abnormal Returns Considering the Alternative Estimation Procedure

Decile[b]	1	2	3	4	5	6	7	8	9	10
1	**23.41**	2.97	4.84	**16.89**	-0.11	14.05*	14.35**	13.74**	8.57*	06.54
2	10.50**	7.14	7.20**	**14.58**	12.21**	7.58	3.24	12.26*	4.62	12.29**
3	**8.08**	3.94	6.07**	2.43	1.12	**12.45**	-0.09	7.83	5.08	6.09
4	7.84**	2.49	3.26	3.38	**6.29**	1.64	1.79	-2.38	3.09	4.72
5	6.12*	1.06	2.51	-0.21	2.59	2.48	4.77	0.63	17.63	6.34
6	-2.13	-1.27	-3.17	-0.10	0.65	-3.70	-4.15	4.47	-2.03	2.62
7	-1.44	-3.10	2.16	-3.66	-0.03	-3.44	-3.04	5.07	23.09	-0.57
8	-0.73	-3.84*	-1.64	-1.57	-4.09	1.32	-6.43**	-5.34	-10.24**	9.24
9	1.88	**-6.69**	-3.47	-1.79	0.54	-5.20	-3.34	-1.57	-3.08	-2.29
10	-5.45	**-8.97**	**-13.11**	-6.15*	-1.68	-9.24**	-6.04	1.64	-2.56	-6.98
Mean(C_2)	**4.82**	-1.68*	-0.65	1.20	1.60	0.74	0.12	**4.29**	4.80**	**5.16**
Mean(R_2)	**10.57**	**9.37**	**5.30**	**3.23**	**3.97**	-1.14	0.63	-2.77**	-2.66**	**-6.31**
Mean(R_3)	**9.56**	**6.55**	2.62**	2.91**	2.11	3.70**	2.57*	-0.01	-1.08	**-6.50**

[a] Other-information decile portfolios and analysts' forecast-dispersion decile portfolios are formed annually by ranking firms according to other information and the standard deviations of analysts' forecast, respectively. In this Table we consider only December 31st fiscal-year-end firms-year. This requirement is necessary once the hedge portfolio has to be assigned and maintained fixed during the buy-and-hold period. After imposing this requirement, considering the estimation procedure of Panel A (B), our sample reduced to $26,006$ $(12,755)$ firms-year observations, in which $24,650$ $(11,447)$ and $23,240$ $(10,164)$ have non-missing size-adjusted abnormal returns for $t+2$ and $t+3$, respectively.

[b] Rows indicate decile portfolios based on other information, and columns indicate decile portfolios based on analysts' forecast dispersion. $*$, $**$, and bold values represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

[c] Mean(C_i) and Mean(R_i) represent the mean of abnormal returns at $t+i$ for the portfolios indicated in columns and rows, respectively . In other words, Mean(C) represents the mean of abnormal returns for decile-portfolios based on analyst's forecast dispersion, and Mean(R) represents the mean of abnormal returns for decile-portfolios based on other information.

Table 8: **The Relation among Persistence Estimation, Earnings, and Analyst Forecast Errors**[a]

	Analysts' Estimated Persistence	
Impact on Earnings	Persistence > 1	Persistence < 1
Negative	Overestimate Forecast Errors < 0 Pessimistic	Underestimate Forecast Errors > 0 Optimistic
Positive	Overestimate Forecast Errors > 0 Optimistic	Underestimate Forecast Errors < 0 Pessimistic

[a] In terms of persistence of the accounting components, the expressions overestimate and underestimate can be related with both positive and negative forecast errors, depending on the impact of the respective accounting component on future earnings. In this table we illustrate a variable with a hypothesized persistence that equals one. Overestimation (underestimation) is related with a persistence greater (smaller) than one in both types of impact on earnings (positive and negative), but not with the same sign of analyst forecast errors.

Table 9: **Descriptive Statistics**

Panel A: Descriptive Statistics of Accounting Fundamentals[a]

Variables[b]	Mean[c]	Std. Dev.	Median	Min.	Q1	Q3	Max.	% Positive
EARN_{t+1}	0.032	0.143	0.051	-1.214	0.011	0.096	0.412	78.63
CFO_t	0.093	0.157	0.101	-3.777	0.050	0.162	0.681	86.52
NAC_t	-0.066	0.076	-0.062	-1.161	-0.101	-0.033	0.815	11.36
ABNAC_t	0.008	0.125	0.012	-4.153	-0.032	0.057	1.447	57.56
BV_t	0.626	0.399	0.562	0.000	0.376	0.790	7.131	100
DIV_t	0.013	0.022	0.000	0.000	0.000	0.019	0.245	48,49

Panel B: Descriptive Statistics of Returns, Analysts, and Other Information Data

Variables[b]	Mean[c]	Std. Dev.	Median	Min.	Q1	Q3	Max.	% Positive
RET_{t+1}	0.179	0.751	0.077	-0.978	-0.185	0.364	26.700	48.43
ABRET_{t+1}	0.050	0.683	-0.035	-1.737	-0.267	0.211	25.962	59.80
CAF_t	0.030	0.150	0.057	-1.982	0.016	0.081	0.603	85.12
ACTUAL_{t+1}	0.026	0.161	0.042	-1.982	0.015	0.081	0.441	84.23
ϵ_t	0.003	0.042	0.000	-0.715	-0.002	0.001	1.852	37.03
ϵ_{x_t}	0.009	0.035	0.004	-1.132	-0.001	0.015	0.921	71.10
ϵ_{V_t}	-0.006	0.053	-0.004	-0.930	-0.016	0.002	1.836	31.97
$\widehat{V}_{t+1}$	0.015	0.130	0.007	-1.495	-0.022	0.052	0.618	56.93
$\widehat{V}^*_{t+1}$	0.021	0.147	0.012	-1.677	-0.020	0.065	0.673	60.31

[a] Our sample was identified by merging firms listed on Compustat and I/B/E/S from 1983 to 2012. Monthly returns data were obtained on CRSP database. In the end, we obtained a sample size of $40,660$ firms-year observations over our 30-year sample period.

[b] Variables definitions:

- EARN_t = income before extraordinary items;
- CFO_t = cash flow from operating activities;
- NAC_t = normal accruals, given by the predicted value of Jones (1991) model, estimated in a panel regression for each 4-digit Sic code;
- ABNAC_t = abnormal accruals, given by the residual of the Jones (1991) model;
- RET_{t+1} = firm's buy-and-hold return for the 12-month period ending three months after the fiscal-year-end;
- ABRET_{t+1} = size-adjusted abnormal return, estimated as the difference between the firm's buy-and-hold return and the buy-and-hold return for the same 12-month period on the market portfolio decile in which the firm belongs;
- CAF_t = consensus analysts' forecast, set as the mean of analysts' forecast;
- ACTUAL_{t+1} = IBES actual earnings;
- $\widehat{V}_{t+1}$ = analysts' expectation of other information, estimated for each 4-digit Sic code as the residuals of the panel regression of consensus analyst forecast on past earnings components, book value, and dividends;
- $\widehat{V}^*_{t+1}$ = other information, estimated for each 4-digit Sic code as the residuals of the panel regression of actual earnings on past earnings components, book value, and dividends;

Table 10: **Mishkin Test and OLS Comparison[a] for Portfolios based on Abnormal Accruals**

Panel A: OLS and Mishkin Test Coefficients for the Entire Sample

Forecasting Coefficient		*Analyst Coefficient*		*$H_0 : \gamma_i^* = \gamma_i$*	*OLS Coefficient*		
Parameter	Estimate[b]	Parameter	Estimate	$\gamma_i^* - \gamma_i$	Parameter	Estimate	$\delta(\gamma_i^* - \gamma_i)^c$
γ_0	-0.0139***	γ_0^*	0.0033	-0.0172***	ϕ_0	0.0025***	0.0025***
γ_1	0.6497***	γ_1^*	0.4803***	0.1694***	ϕ_1	-0.0245***	-0.0245***
γ_2	0.4166***	γ_2^*	0.3067***	0.1099***	ϕ_2	-0.0159***	-0.0159***
γ_3	0.2888***	γ_3^*	0.2092***	0.0796***	ϕ_3	-0.0115***	-0.0115***
γ_4	0.0031**	γ_4^*	0.0258***	-0.0227***	ϕ_4	0.0033***	0.0033***
γ_5	0.2501***	γ_5^*	0.1722***	0.0779	ϕ_5	-0.0113	-0.0113

Panel B: OLS and Mishkin Test Coefficients for the Positive Abnormal-Accruals Portfolio

Forecasting Coefficient		*Analyst Coefficient*		*$H_0 : \gamma_i^* = \gamma_i$*	*OLS Coefficient*		
Parameter	Estimate	Parameter	Estimate	$\gamma_i^* - \gamma_i$	Parameter	Estimate	$\delta(\gamma_i^* - \gamma_i)$
γ_0	0.0070***	γ_0^*	0.0117*	-0.0047	ϕ_0	0.0005	0.0005
γ_1	0.6226***	γ_1^*	0.5162***	0.1064***	ϕ_1	-0.0119***	-0.0119***
γ_2	0.4350***	γ_2^*	0.4070***	0.0280	ϕ_2	-0.0031	-0.0031
γ_3	0.3267***	γ_3^*	0.2603***	0.0664**	ϕ_3	-0.0074**	-0.0074**
γ_4	-0.0045	γ_4^*	0.0190***	-0.0235***	ϕ_4	0.0026***	0.0026***
γ_5	0.1598***	γ_5^*	0.2700**	-0.1102	ϕ_5	0.0123	0.0123

Panel C: OLS and Mishkin Test Coefficients for the Negative Abnormal-Accruals Portfolio

Forecasting Coefficient		*Analyst Coefficient*		*$H_0 : \gamma_i^* = \gamma_i$*	*OLS Coefficient*		
Parameter	Estimate	Parameter	Estimate	$\gamma_i^* - \gamma_i$	Parameter	Estimate	$\delta(\gamma_i^* - \gamma_i)$
γ_0	-0.0419***	γ_0^*	-0.0103**	-0.0316***	ϕ_0	0.0059***	0.0059***
γ_1	0.6771***	γ_1^*	0.4809***	0.1962***	ϕ_1	-0.0369***	-0.0369***
γ_2	0.4768***	γ_2^*	0.2007***	0.2761***	ϕ_2	-0.0519***	-0.0520***
γ_3	0.2102***	γ_3^*	0.1675***	0.0427**	ϕ_3	-0.0080**	-0.0080**
γ_4	0.0153***	γ_4^*	0.0385***	-0.0232***	ϕ_4	0.0043***	0.0043***
γ_5	0.3614***	γ_5^*	0.1673	0.1941	ϕ_5	-0.0365	-0.0365

[a] Panel A, B and C present results obtained for the reformulated Mishkin test applied to the regression system composed by the forecasting and analyst equations, as described in equations 33 and 34, and for the estimation of the equivalent OLS model described in equation 26. Variables definitions are present in Table 1.

Forecasting Equation : $\text{ACTUAL}_{t+1} = \gamma_0^* + \gamma_1\text{CFO}_t + \gamma_2^*\text{NAC}_t + \gamma_3^*\text{ABNAC}_t + \gamma_4^*\text{BV}_t + \gamma_5^*\text{DIV}_t + e_{t+1}$

Analyst Equation: $\epsilon_{t+1} = \alpha + \delta\,(\text{ACTUAL}_{t+1} - \gamma_0 - \gamma_1\text{CFO}_t - \gamma_2\text{NAC}_t - \gamma_3\text{ABNAC}_t - \gamma_4\text{BV}_t - \gamma_5\text{DIV}_t) + \epsilon_{t+1}$

OLS Equation: $\epsilon_{t+1} = \phi_0 + \phi_1\text{CFO}_t + \phi_2\text{NAC}_t + \phi_3\text{ABNAC}_t + \phi_4\text{BV}_t + \phi_5\text{DIV}_t + u_{t+1}$

[b] $*$, $**$, and $***$ represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

[c] The coefficient δ of the analyst equations of Panel A, B and C equals -0.2233, -0.1119, and -0.1882, respectively, and are all significants at 1% level.

Table 11: **The Influence of Abnormal Accruals on Analyst Forecast Errors**[a]

Panel A: OLS Regression Considering Portfolios Based on Abnormal Accruals

Variable	Parameter	Estimate[b]	Std. Error	$P > \|t\|$	Estimate	Std. Error	$P > \|t\|$
CFO$_t$	ϕ_1	-0.0245***	0.0014	0.000	-0.0235***	0.0014	0.000
NAC$_t$	ϕ_2	-0.0159***	0.0029	0.000	-0.0149***	0.0030	0.000
ABNAC$_t$	ϕ_3	-0.0115***	0.0018	0.000	-0.0088	0.0289	0.765
Neg.ABNAC$_t$	ϕ_4				0.0061	0.0291	0.835
High	ϕ_5				0.0041***	0.0005	0.000
High.ABNAC$_t$	ϕ_6				0.0572	0.0377	0.129
High.Neg.ABNAC$_t$	ϕ_7				-0.0727**	0.0378	0.055
BV$_t$	ϕ_8	0.0033***	0.0005	0.000	0.0025***	0.0005	0.000
DIV$_t$	ϕ_9	-0.0113	0.0098	0.230	-0.0067	0.0098	0.493
	ϕ_0	0.0025***	0.0005	0.000	0.0016***	0.0005	0.001

[a] Panels A and B present results for the estimation of the following model:

$\epsilon_{t+1} =$

$\phi_0 + \phi_1 \text{CFO}_t + \phi_2 \text{NAC}_t + \phi_3 \text{ABNAC}_t + \phi_4 \text{Neg.ABNAC} + \phi_5 \text{High} + \phi_{56} \text{High.ABNAC}_t + \phi_7 \text{High.Neg.ABNAC}_t + \phi_8 \text{BV}_t + \phi_9 \text{DIV}_t + u_{t+1}$

Variable definitions are present in Table 9. High is a dummy set as $1(0)$ for firms-year in the up (bottom) 30 percentile of the ranked abnormal accruals (in absolute value). Neg is a dummy that indicates firms-year with negative abnormal accruals.

[b] $*$, $**$, and $***$ represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.

Table 12: **Testing Analyst Bias according to Other Information**[a]

Panel A: Analysts' Expected Other Information Regressed on Realized Other Information

Variable	Parameter	Estimate[b]	Std. Error	$P > \|t\|$	Estimate	Std. Error	$P > \|t\|$
Neg	β_1	-0.0036***	0.0009	0.000	-0.0035***	0.0009	0.000
$\widehat{V}_{t+1}$	β_2	0.8513***	0.0050	0.000	0.8637***	0.0052	0.000
Neg.$\widehat{V}_{t+1}$	β_3	-0.0630***	0.0156	0.0000	-0.0937***	0.0167	0.000
CFO$_t$	β_4				0.0329***	0.0049	0.000
NAC$_t$	β_5				0.0383***	0.0051	0.000
ABNAC$_t$	β_6				0.0045	0.0044	0.307
BV$_t$	β_7				-0.0051***	0.0011	0.000
DIV$_t$	β_8				0.0121**	0.0133	0.363
	β_0	-0.0033***	0.0003	0.000	-0.0021***	0.0008	0.009
F Statistic		35,305.26			13,635.46		
Adj R-squared		87.55%			87.73%		

Panel B: The Influence of Forecast Dispersion on Other Information Bias

Variable	Parameter	Estimate[b]	Std. Error	$P > \|t\|$	Estimate	Std. Error	$P > \|t\|$
Neg	β_1	-0.0002	0.0007	0.811	-0.0008	0.0007	0.215
Neg.High	β_2	-0.0064***	0.0018	0.000	-0.0044**	0.0018	0.013
$\widehat{V}_{t+1}$	β_3	0.8513***	0.0050	0.000	0.8629***	0.0052	0.000
Neg.$\widehat{V}_{t+1}$	β_4	0.0444***	0.0131	0.001	0.0125	0.0138	0.363
Neg.High.$\widehat{V}_{t+1}$	β_5	-0.1964***	0.0265	0.000	-0.1887***	0.0265	0.000
CFO$_t$	β_6				0.0301***	0.0046	0.000
NAC$_t$	β_7				0.394***	0.0050	0.000
ABNAC$_t$	β_8				0.0045	0.0042	0.289
BV$_t$	β_9				-0.0043***	0.0011	0.000
DIV$_t$	β_{10}				0.0208	0.0135	0.124
	β_0	-0.0033***	0.0003	0.000	-0.0023***	0.0008	0.003
F Statistic		22,983.90			11,924.19		
Adj R-squared		88.10%			88.26%		

[a] This table presents results for the estimation of the models described bellow, estimated using the robust OLS estimator:

$\widehat{V}_{t+1} = \beta_0 + \beta_1\text{Neg} + \beta_2 V_{t+1} + \beta_3\text{Neg}.V_{t+1} + \beta_4\text{CFO}_t + \beta_5\text{NAC}_t + \beta_6\text{ABNAC}_t + \beta_7\text{BV}_t + \beta_8\text{DIV}_t + e_{t+1}$

$\widehat{V}_{t+1} = \beta_0 + \beta_1\text{Neg} + \beta_2\text{Neg.High} + \beta_3 V_{t+1} + \beta_4\text{Neg}.V_{t+1} + \beta_5\text{Neg.High}.V_{t+1} + \beta_6\text{CFO}_t + \beta_7\text{NAC}_t + \beta_8\text{ABNAC}_t$
$+\beta_9\text{BV}_t + \beta_{10}\text{DIV}_t + e_{t+1}$

Variable definitions are present in Table 1. Neg is a dummy set as 1 if V$_{t+1}$ is negative, and 0 otherwise. High is a dummy set as 1 for firms-year in the up 30 percentile of ranked analyst forecast dispersion.

[b] $*$, $**$, and $***$ represent significance at 0.10, 0.05, and 0.01 level, respectively, based on a two-tailed t-test.