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THE READABILITY OF MANAGEMENT DISCUSSION AND ANALYSIS (MD&A): determinants and consequence

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Tese apresentada ao Programa de Doutorado em Ciências Contábeis e Administração de Empresas, 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: Dr. Fábio Moras da Costa

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To my family, friends and professors.

RESUMO

Este estudo explora os determinantes e efeitos da *readability* da seção de *Management Discussion and Analysis* (*MD&A*) e está dividido em três partes. O primeiro artigo investiga se os gestores, depois de engajarem em práticas de gerenciamento de resultado para bater ou superar o benchmark (resultado do ano anterior), usam estrategicamente atividades de *corporate disclosure* com objetivo de esconder o meio utilizado para alcançar seus objetivos. Especificamente, eu comparo o nível de *readability* da seção de *MD&A* para grupos de firma com boas notícias para comunicar para o mercado, mas com diferentes níveis de gerenciamento de resultado. Eu uso o *Fog index* do documento como *proxy* para *readability*. Os resultados mostram que o nível de *readability* é influenciado pelo tipo de notícia a ser comunicada para o mercado e também é influenciado pelas práticas de gerenciamento de resultado. O segundo artigo analisa se o nível de *readability* da seção de *MD&A* pode ser utilizado para identificar erros contábeis. Eu uso a base de dados de *AAER* como evidencia de firmas com erros, o modelo *F-score* proposto por Dechow et al. (2011) como modelo para prever firmas com erros e o *Fog index* como *proxy* para *readability*. Os resultados sugerem que a *readability* tem um efeito direto e positivo na probabilidade de detectar firma AAER. Além disso, o uso de *readability* como um determinante de firmas com erro melhora a capacidade de predição de firmas AAER comparado com os modelos anteriores apresentados na literatura. O terceiro artigo investiga se o nível de *readability* influencia a má precificação do resultado (lucro) pelo mercado. Mais especificamente, eu analiso se os investidores estão aptos a entenderem a persistência do resultado para firmas deficitárias e firmas lucrativas com diferentes níveis de *readability* nas demonstrações contábeis. Eu uso o *Fog index* como *proxy* para *readability* e o teste Mishkin (1983) para identificar se o mercado incorpora corretamente no preço a persistência dos resultados correntes. Os resultado indicam que para firmas com prejuízo a *readability* afeta a má precificação do resultado. Mais especificamente, para as firmas com prejuízo e com seção de *MD&A* mais difíceis de ler o mercado subestima a persistência do resultado, ao passo que para firmas com prejuízo e com uma informação mais fácil de ler o mercado precifica corretamente. Entretanto, para firmas lucrativas os resultados não confirmam que a *readability* afeta a má precificação do resultado.

Palavavras-chave: gerenciamento de resultado, erros contábeis, *readability, strategic disclosure, earnings mispricing.*

ABSTRACT

This study explores determinants and effects of Management Discussion and Analysis (MD&A) readability and it is divided in three papers. The first paper investigates whether managers, after engaging in earnings management practices to meet or beat the last earnings benchmark, use strategically corporate disclosure activities in order to hide the path taken to achieve their goals. Specifically, I compare the level of readability of MD&A section for groups of firms which have good news to communicate to the market, but with different levels of earnings management. I use the Fog index of the document as the proxy for readability. Results show that the level of readability is influenced by the type of the news to communicate to the market and it is also influenced by earnings management practices. The second paper analyzes whether the readability level of MD&A section can be used to identify material accounting misstatements. I use the AAER database as evidence of misstating firms, the F-score model proposed by Dechow et al. (2011) as predicting model of misstating firms and the Fog index as proxy for readability. The results suggest that readability has a direct and positive effect on the likelihood of detecting an AAER firm. Moreover, the use of readability as determinant of misstating firm improves the predictability of detecting AAER firms compare to prior models in the literature. The third paper investigates whether the level of readability influences the earnings mispricing by the market. More specifically, I test whether investors are able to understand the earnings persistence for loss and profit firms with different level of financial statements' readability. I use the Fog index as the proxy for readability and the Mishkin (1983) test to identify whether the market correctly incorporate in price the persistence of current earnings. The results indicate that for loss firms the readability affects the earnings mispricing. More specifically, for loss firms with MD&A section harder to read the market understates earnings' persistence, whereas for loss firms with more readable information the market price correctly. However for profit firms the results do not confirm that readability affect earnings mispricing.

Keywords: *readability, strategic disclosure, earnings management, accounting misstatements, earnings mispricing.*

CONTENTS

CONTENTS

INTRODUCTION

This dissertation identifies and analyzes some determinants and consequences of readability of Management Discussion and Analysis (MD&A). According to the SEC (2003) the MD&A is the section where managers should present a discussion and analysis about the company's business, providing an understanding of financial conditions, changes in finance conditions and results of operations. Readability means the ease which text can be read and understood. Therefore, this dissertation explores the possibility of MD&A readability be influenced by managers' discretion and which consequences this discretion can lead to market. This study is divided in three papers. The first two papers explore the determinants of MD&A readability. On the other hand, the third paper analyzes the consequence of MD&A readability.

The first and leading paper investigates whether managers, after engaging in earnings management practices to meet or beat the last earnings benchmark, use strategically corporate disclosure activities in order to hide the path taken to achieve their goals. More specifically, I compare the level of readability of MD&A section for groups of firms which have good news to communicate to the market, but with different levels of earnings management. I use the Fog index of the document as the proxy for readability. Results show that the level of readability is influenced by the type of the news to communicate to the market and it is also influenced by earnings management practices.

Based on that financial misreporting is a critical point to the efficient function of capital market, the second paper analyzes whether the readability level of MD&A section can be used to identify material accounting misstatements. To address the

research question I use the AAER database as evidence of misstating firms and the F-score proposed by Dechow et al. (2011) to predict misstating firms. I also use the Fog index to measure the readability of MD&A section as in paper one. Basically, the paper proposes a new approach of Dechow et al. (2011) model adding another dimension related to readability which was not contemplated on prior models. The results suggest that readability can be used to identify accounting misstatements. More specifically, the readability has a direct and positive effect o the likelihood of detecting an AAER firm. Moreover, the use of readability as determinant of misstating firm improves the predictability of detecting AAER firm compare to prior models in the literature.

The third, differently of the first two, analyzes the consequence of the readability of MD&A section. The main objective of the paper is to investigate whether the level of readability influences earnings by investors. Specifically, I test whether investors are able to understand the earnings persistence for loss and profit firms with different level of financial statements' readability. As in prior papers, I also use the Fog index to measure the readability of MD&A section. Additionally, aiming to investigate whether the market correctly incorporate in price the persistence of current earnings I use de Mishkin (1983) test. The results indicate that the readability affects the earnings persistence for loss firms. More specifically, for loss firms with MD&A section harder to read the market understates earnings persistence. On the other hand, for loss firms with annual report easier to read the market price correctly. However for profit firms the results do not confirm that readability affect earnings mispricing.

Chapter 1

1 IS GOOD NEWS ALWAYS EASIER TO READ?

1.1INTRODUCTION

The main objective of this paper is to analyze whether managers, after engaging in earnings management practices to meet or beat the last earnings benchmark, use strategically corporate disclosure activities in order to hide the path taken to achieve their goals. In particular, I compare the readability level of Management Discussion and Analysis (MD&A) section of two groups of firms which have good news to communicate to the market. The groups are segregated by the probability (high or low) of having met or beat the benchmark through earnings management practices. Generally, I expect that the group of firms with high probability present annual report (MD&A section) which is more complicated or costly to read, because managers have an incentive to hide adverse information relative to the path taken to achieve their goals. On the other hand, I expect that the group composed by firms with low probability has a more readable annual report, because managers have incentives to send signals to the market about their true type.

Prior literature suggests that managers strategically use corporate disclosure activity in order to mislead or to influence the investors' understanding about the firm's state (e.g. SCHRAND and WALTHER, 2000; LANG and LUNDHOLM, 2000). Empirical evidence show that managers use different mechanisms to mislead outsiders as to select the lowest possible benchmark for evaluating current earnings (SCHRAND and WALTHER, 2000), or to influence the frequency and the amount of disclosure provided to the market (LANG and LUNDHOLM, 2000), or to use

complicated language to hide the transitory nature of good news or permanent nature of bad news (LI, 2008).

Prior evidence also suggest that managers take actions to avoid small negative earnings surprise or to miss earnings benchmarks (e.g. BURGSTAHLER and DICHEV, 1997; BARTOV et al., 2002; MATSUMOTO, 2002). This type of behavior are confirmed by CFOs who admit that they would take real economic actions such as delaying maintenance or advertising expenditure to meet short-term earnings benchmarks (GRAHAM et al., 2005). According to the survey by Graham et al (2005), the main motivations for why managers might exercise accounting discretion to achieve some desirable earnings goals are related to build credibility with capital market, to maintain or to increase stock price, and to improve the external reputation of the management team. The top two consequences of a failure to meet earnings benchmarks, according to Graham et al (2005), are an increase in the uncertainty about future prospects and a perception among outsiders of the existence of previous unknown problems.

Additionally, there are wide documented evidence about earnings management practices and their consequences associated with several outcomes as to get modified audit opinions (e.g. FRANCIS and KRISHNAN, 1999, BRADSHAW et al., 2001), market valuations (MYERS et al., 2007), cost of equity capital (e.g. FRANCIS et al., 2004, BHATTACHARYA et al., 2003), and cost of debt capital (e.g. FRANCIS et al., 2005). However, to my knowledge, there is no evidence about what is the effect of earnings management to meet or beat the last earnings benchmark on strategic disclosure.

Specifically, there is one issue that has not been addressed in the disclosure literature yet. If good current reported earnings are partially due to strategic

manipulation, do managers want to make annual reports easier to read? Are they willing to give the same or more information to show good performance even that information might give indications that they use earnings management practices? Accordingly, in this situation managers face a conflict between the desire to convince the market that their performance is good and, at the same time, the need to hide the chosen path to achieve firms' result. Therefore, this paper fills this gap in the literature.

Additionally, this paper analyzes more carefully an alternative explanation proposed by Bloomfield (2008), namely "ontology", related to Li's (2008) results. According to Bloomfield (2008) the relation between poor performance and transitory earnings with less readable annual reports could be attributed to the difficulty of explaining these unusual events and not necessarily to the managers' discretion. I control this effect, once I compare the readability level of two different groups of firms respect to the probability of having met or beat the benchmark through earnings management practices, but both with good news to communicate to the market.

To address this research problem my analysis focuses on the 10-K report (mandatory disclosure), more specifically on Management Discussion and Analysis section (MD&A). According to the SEC (2003) the MD&A is the section where managers should present a discussion and analysis about the company's business, providing an understanding of financial conditions, changes in finance conditions and results of operations. Therefore, the MD&A section represents a channel in which managers have to clarify or deepen some important financial points in a narrative form, which readers should know to better evaluate the real financial condition of the firm. This channel is subject to managers' discretion once managers can influence, at

least in part, the amount of information, the presentation form, or the writing complexity of the report.

To test the readability level of the MD&A, I use the Fog index. According to Li (2008) the Fog index is a measure which indicates the number of years of formal education a reader of average intelligence would need to read the text once and understand that piece of writing with its word-sentence workload.

I use the last-year earnings per share as the earnings benchmarks for two reasons. First, because in the MD&A section, the usually comparison made by managers is whether firm is above or below the numbers recorded in the previous years. Although, others benchmarks as analyst consensus are important and common in researches which involve earnings benchmark, I do not use alternative metrics because their relation with MD&A section are not direct as last-year earnings. The second reason is related to the survey by Graham et al (2005), which highlight same quarter last year EPS as the most important earnings benchmark for 85.1% of managers interviewed.

I segregate groups of firms by their distance from the benchmark: firms with bad news, firms with just miss benchmark news, firms with suspect good news and firms with good news. For the main analysis I focus on the group composed by firms with suspect good news, which meet or beat the benchmark by managing upward earnings. After that, I use the Jones (1991) model to calculate the earnings management by accruals and consequently to define which firms have higher and lower probability to use discretion on their earnings to achieve the earnings benchmark. I use variations from Jones (1991) model in the robustness test.

My results indicate that the level of readability is influenced by the type of the news to communicate to the market and it also influenced by the earnings

management practices. Firms with suspect good news have on average MD&A section less readable than firms with good news and even less readable than firms with bad news. Firms with suspect good news and with high probability to meet or beat the benchmark through earnings management practices have on average MD&A section less readable than firms with low probability, in other words the readability level is increasing in the level of earnings management.

My analysis contributes in different ways to the literature. First, it provides more evidence, in line with Lang and Lundholm (2000), that strategic disclosure or corporate disclosure activities are not just influenced by firms' performance. Specifically, my paper shows that actions (earnings management decision) taken by managers to achieve the desired final result influence the readability level of the financial report.

The second contribution of the paper is provide additional evidence, on prior literature (e.g. BURGSTAHLER and DICHEV, 1997; BARTOV et al., 2002; MATSUMOTO, 2002, FRANKEL et al., 2010), related to managers' behavior around earnings benchmarks by showing that there is an asymmetric effect around these point on readability level of MD&A section.

Third, the paper refines the prior report analysis in the readability literature (e.g. LI, 2008) by promoting a more accurate analysis about alternative explanation, namely "ontology", presented by Bloomfield (2008). The results indicate that the level of readability can be partly explained by managers' discretion and not totally attributed to unusual events.

The remainder of the paper is organized in four sections. Section 2 provides a background about earnings management and strategic disclosure literature, and hypotheses development. The research design is presented in Section 3, where I

describe the sample composition and the main tests. Next, Section 4 provides results and analyses. Finally, conclusions, limitations and suggestions for future research are presented in Section 5.

1.2 BACKGROUND AND HYPOTHESES DEVELOPMENT

1.2.1 Earnings Management and Earnings Benchmarks

There is a wide literature about earnings management which document evidence that manager use accounting choice under GAAP framework and/or alter normal operational practices in order to meet or beat earnings benchmarks. In a survey with more than 400 executives Graham et al. (2005) find evidence that the motivations to meeting earnings benchmarks are: (i) to build credibility with the capital market; (ii) to maintain or increase stock price, and (iii) the external reputation of management team, to 86.3%, 82.2% and 77.4% of managers, respectively. On the other hand, the top two consequences of failure to meet earnings benchmarks are increase in the uncertainty about future prospect and the perception among outsiders that there are unknown problems at the firm (GRAHAM et al., 2005).

Empirical evidence show that firms manage reported earnings to avoid earnings decrease and losses. One of the prior studies is Burgstahler and Dichev (1997), which find evidence that two components of earnings, cash flow from operations and change in working capital, are used to do not show small decreases in earnings and small losses. More specifically, Ayers et al. (2006) find evidence consistent with an association between discretionary accruals and meeting or beating analyst forecasts. Firms also make real decision to meet analyst forecast such as

repurchasing stock (HRIBAR et al., 2006), or selling assets or marketable securities (HERRMANN et al., 2003).

1.2.2 Strategic Disclosures

Although Clarkson et al. (1999) find evidence that MD&A, as part of a mandatory report (10-K), is managed in a fashion similar to other well-disclosure channels, researchers have been focused on voluntary disclosures (e.g. press releases, conference calls) to discuss managers' disclosure decisions (e.g. LANG and LUNDHOLM, 2000; JO and KIM, 2007; FRANCIS et al., 2008). An additional feature presented in these papers is the use of disclosure frequency as the proxy for disclosure quality. Jo and Kim (2007) recognize that this proxy not necessarily measure disclosure quality, once frequent disclosure with low information content can cumulatively provide less information than a single highly informative disclosure.

Considering these issues, there is some empirical evidence that managers strategically use annual reports to mislead or to influence investors' understanding about firms' performance. Lang and Lundholm (2000), based on a small sample, find that disclosure activity of issuing firms (SEO – Second Equity Offering) and non-issuing are very comparable in terms of frequency and tone up to six months before the offering is announced. However, beginning six months before the SEO event, the issuing firms dramatically increase their disclosure activity relative to the prior six-month period and even relative to the non-offering firms.

Jo and Kim (2007) are the first to find evidence about the relation between disclosure frequency and earnings management, arguing that in general disclosure increase transparency and consequently it mitigates the incentive to manage earnings, because increased transparency helps investors detect earnings

management practices. They use the number of distinct press releases and find that earnings management (discretionary accruals) is a decreasing function of the persistent level of disclosure, and earnings management is positively associated with a non-persistent disclosure increase.

In related research, Francis et al. (2008) find evidence of a complementary relation between voluntary disclosure and earnings quality. Based on a coded index of financial information from annual reports they show that firm with better earnings quality issue more expansive voluntary disclosures than firms with poorer earnings quality. Another related paper, Frankel et al (2010) find an asymmetric increase (decrease) in call length (forecasting propensity) for firms that miss analyst expectations by 1 cent compared with change in adjacent 1-cent interval.

In summary, there are strong evidence of earnings management to beat or meet earnings benchmarks and the use of strategic disclosures by managers. Building on the above discussion, but focusing on mandatory reporting (MD&A section), using a set of firms that have different types of news to communicate to the market, using alternative proxy for disclosure quality that no disclosure frequency, and treating for the level of earnings management, I hypothesize that:

H1(a): Firms with bad news, on average, present less readable MD&A section than firms with good news.

H1(b): Firms that just missed the earnings benchmark, on average, present MD&A section less readable than firms with good news and bad news.

H1(c): Firms with suspect good news, on average, present MD&A section less readable than firms with good news and bad news.

H2: Firms with suspect good news and with high probability to beat or meet last earnings benchmark through earnings management present MD&A section less readable than firms with suspect good news and with low probability.

H3: The low readability of firms with suspect good news is increasing on the earnings management level.

1.3 RESEARCH DESIGN

1.3.1 Data and sample description

The sample is composed by all firms with available data necessary to estimate the proxies of readability and their controls as well as variables for the earnings management models, between 2000 and 2012. The 2000 cutoff is related to greater availability of 10-K report for the calculation of Fog index. An additional requirement to have *cik* (central index key - SEC) is necessary to obtain financial statements from the Edgar database.

I exclude firms from the financial service (SIC 6000-6999) and utility service (SIC 4400-5000) industries because disclosure requirements and accounting rules are significantly different for these industries. After the exclusion process, the final sample is composed by 26,967 firm-year observation as showed in Table 1.

TABLE 1: SAMPLE SELECTION

SAMPLE	N
All U.S. firm-year on Compustat	109,197
Less financial service industry and utility service	(24,507)
Less unable to obtain financial statement/MD&A section on Edgar	(57,723)
Firm-year observations	26,967
Unique firms	4,855

First, I segregate the sample based on the distance between reported earnings and the earnings benchmark (last-year earnings) to analyze the effect by penny. After that, I segregate the sample in four subsamples: (i) firms with bad news; (ii) firms with just miss earnings benchmark news; (iii) firms with suspect good news and; (iv) firms with good news. The first subsample (*bad*) is defined as all firms that not meet or beat the benchmark and which are not included on the just miss the benchmark subsample. The second subsample (*miss*) is defined as all firms that not meet the benchmark by one cent (Model 1), by two cents (Model 2) and by three cents (Model 3). The third subsample (*suspect*) is defined as all firms just beat or meet the earnings benchmark by one cent (Model 1), by two cents (Model 2) and by three cents (Model 3). Finally the forth subsample (*good*) is defined as all firms with results above the earnings benchmark and which are not include on the suspect good news subsample.

To address the main objective of this paper about suspect firms which engaging in earnings management practices to meet or beat a benchmark, I segregate the subsample of suspect good news on firms with high probability to meet or beat the benchmark trough earnings management practices and firms with low probability to meet or beat the benchmark through earnings management practices. Firms with high probability are defined as all firms in the suspect good news subsample which have positive discretionary accruals and firms with low probability are defined as all firms in the suspect good news subsample which have negative discretionary accruals.

Finally, to address the last analysis about whether the readability level is increasing on the earnings management level, I segregate the subsample of firms with suspect good news and with high probability to meet or beat the last earnings

benchmark in to news subsample: firms below the median of positive discretionary accruals and above the median.

1.3.2 Proxy for Readability

Following Li (2008) I use the Fog index as the proxy for readability. The Fog Index measures the number of years of formal education a reader of average intelligence would need to read the text once and understand that piece of writing with its word-sentence workload. The index is a function of syllables per word and words per sentence and it is calculated as:

$$FOG = (words\_per\_sentence + percent\_of\_complex\_words) * 0.4 \quad (1.1)$$

Complex words are defined as words with three syllables or more. Higher FOG index means that the text is less readable or more difficult to understand. The Fog index is calculated based on the MD&A section of the 10-K report. Using the Perl programming language, I download all available 10-k filings from Edgar and perform a search to obtain the MD&A section and calculate the FOG index.

1.3.3 Earnings Management Proxies

Following prior studies (JONES 1991, DECHOW et al. 1995, DECHOW and DICHEV 2002), I use discretionary accruals as the proxy for accrual-based earnings management. In particular, I estimate discretionary accruals using the Jones (1991) model.

$$Accruals_t = \alpha_0 + \alpha_1(1/A_{t-1}) + \alpha_2(\Delta REV_t) + \alpha_3(PPE_t) + \varepsilon_t \quad (1.2)$$

where $Accruals_t$ is equal the earnings before extraordinary items and discontinued operations minus the operating cash flows reported in the statement of cash flows in

year *t* scaled by total assets at *t-1*, ΔREV_t is equal revenues in year *t* less revenues in year *t-1* scaled by total assets at *t-1*, and PPE_t is equal gross property plant and equipment in year *t* scaled by total assets at *t-1*. The estimated residuals, capturing discretionary accruals, and represent the proxy for accrual-based earnings management. I estimate the regression (1.2) cross-sectionally by industry and years with at least 15 observations.

As a robustness test I also use a modified version of the Jones (1991) model proposed by Dechow et al. (1995). The modified version is very similar to the original version, but with an adjustment on the changes in revenues for the change in receivables. Implicitly the original model assumes that managers do not exercise discretion over revenue. On the other hand, the modified version, implicitly relax this assumption with respect to revenue on credit sales. As in Jones (1991) model the discretionary accruals are calculated as the residuals of equation (1.3).

$$Accruals_t = \alpha_0 + \alpha_1(1/A_{t-1}) + \alpha_2(\Delta REV_t - \Delta REC_t) + \alpha_3(PPE_t) + \varepsilon_t \qquad (1.3)$$

where all variables definitions are similar of Jones (1991) model except by the new variable ΔREC_t which is equal receivables in year *t* less receivables in year *t-1* scaled by total assets at *t-1*. I also estimate the regression (1.3) cross-sectionally by industry and years with at least 15 observations.

As an additional robustness test, I conduct a test using performance-matched discretionary accruals following Kothari, Leone and Wasley (2005) procedure. I match each firm-year observation with another from the same year and Fama-French industry code with the closest return on assets in the last year. Following Kothari et al. (2005) I define the Jones-model performance-matched discretionary accruals as the Jones-model discretionary accrual minus the matched firm's Jones-model discretionary accrual.

1.3.4 Main Tests

Before define the final rule to segregate the four groups: bad, miss, suspect and good, I analyze the “penny effect”. The objective in this analysis is to demonstrate that the effect is concentrated around the last-year earnings benchmark and the effect is dissipated after some pennies from zero point (i.e., no difference between actual and last-year earnings). To examine the penny effect and readability characteristics, I estimate the following cross-sectional model:

$$Fog_{it} = \beta_0 + \beta_1 bad_{it} + \beta_2 miss7_{it} \beta_3 miss6_{it} + \beta_4 miss5_{it} + \beta_5 miss4_{it} + \beta_6 miss3_{it} + \beta_7 miss2_{it} + \beta_8 miss1_{it} + \beta_9 make0_{it} + \beta_{10} make1_{it} + \beta_{11} make2_{it} + \beta_{12} make3_{it} + \beta_{13} make4_{it} + \beta_{14} make5_{it} + \beta_{15} make6_{it} + \beta_{16} make7_{it} + \sum_{c=17}^{28} \beta_c controls_{it} + \varepsilon_{it} \quad (1.4)$$

In the model (1.4), the dependent variable, Fog_{it}, is the Fog Index of the MD&A section from the 10-K report. As independent variables, I define the group *bad* as all observations below minus seven cents, firms which miss the benchmark by seven to one cent are represents by *miss7, miss6, miss5, miss4, miss3, miss2, miss1*, respectively, firms which met or beat the benchmark by zero to seven are represents *by make0, make1, make2, make3, mak4, make5, make6, make7,* respectively. Finally, all observations above seven cents are defined as the group *good,* which is the control group. Each group is defined as a dummy variable equals one if the observation meets the group definition or zero otherwise.

The β_1 coefficient represents the readability incremental effect (Fog) of bad news subsample on good news subsample. The β_2 to β_8 coefficients represent the readability incremental effect (Fog) of subsamples which missed last earnings benchmark by seven to one cent on good news subsample. The β_9 to β_{16} coefficients represent the readability incremental effect (Fog) of subsamples which meet or beat last-year earnings benchmark by zero to seven cents on good news subsample. I

expect that coefficients of groups closer from the zero point be positive and statistically significant.

The model (1.4) also contains a large set of control variables[1] suggested by Li (2008), which are potentially determinants of the readability. Specifically, size (*SIZE)* is the logarithm of the market value of equity at the end of the fiscal year; market-to-book (*MTB)* is the market value of equity plus book value of liability and divided by the book value of total assets at the end of the fiscal year; firm age (*AGE)* is the number of years since a firm's first appearance in the CRSP monthly stock return files; special items (*SI)* is the amount of special item scaled by book value of assets; return volatility (*RET_VOL*) is the standard deviation of the monthly stock returns in the prior year; earnings volatility (*EARN_VOL*) is the standard deviation of the operating earnings during the prior five fiscal years; business segments (*NBSEG*) is the logarithm of the number of business segments; geographic segments (*NGSEG*) is the logarithm of the number of geographic segments; non-missing items (*NITEMS*) is the logarithm of the number of non-missing items in Compustat; merged-and-acquisition (*MA*) is a dummy variable equal 1 for a year in which a company appears in the SDC Platinum M&A dataset as an acquirer and 0 otherwise; seasoned equity offering (*SEO*) is a dummy variable equal 1 for a year in which company has a common equity offering in the secondary market according to the SDC Global New Issues database and 0 otherwise; Delaware incorporation (*DL*) is a dummy variable if firm is incorporated in Delaware and 0 otherwise. In addition, I also follow Li (2008) and include year and industry fixed effect.

After this first analysis based on penny effect, I define the four interest groups for the next analyses. All analyses from this point are presented in three ways to

[1] For more information about control variables see Li (2008).

ensure more robustness to the results. The group *bad* is redefined as all observations: (a) below minus one cent, (b) below two cents, and (c) below three cents, each case represents one separate analysis. The group *miss* is defined as all firms which miss the last-earnings benchmark by: (a) one cent, (b) one to two cents, and (c) one to three cents. The group *suspect* is defined as all firms which beat or meet the last-earnings benchmark by: (a) zero to one cent, (b) by zero to two cents, and (c) by zero to three cents. Finally, the group good is defined as all firms which are above last-year earnings benchmark by: (a) one cent, (b) two cents, and (c) three cents. As in the penny effect analysis each group is defined as a dummy variable. To examine the relation between the type of news (bad, miss, suspect and good) and readability characteristics, I estimate the following cross-sectional model to test my first hypothesis:

$$Fog_{it} = \beta_0 + \beta_1 bad + \beta_2 miss + \beta_3 suspect + \sum_{c=4}^{15} \beta_c controls_{it} + \varepsilon_{it} \quad (1.5)$$

In the model (1.5) the β_1 coefficient represents the readability incremental effect (Fog) of bad news subsample on good news subsample. The β_2 coefficient represents the readability incremental effect (Fog) of just miss benchmark news subsample on good news subsample. The β_3 coefficient represents the readability incremental effect (Fog) of suspect good news subsample on good news subsample. I expect that β_1, β_2 and β_3 be positive and statistically significant. Also I expect that β_2 be greater than β_1, once the market believes that most firms can “find the money” to hit earnings benchmark and hence investor can interpret as evidence of hidden problems at the firm (Graham et al 2005). I expect that β_3 be greater than β_1, once firms with suspect good news have more to hide to the market than firms with bad news. It is important to highlight that firms with suspect good news are propensity to

be firms which have bad news to communicate to market, but after the use of earnings management practices they change their type of new to a good new.

The next analysis is to examine the relation between the type of news (*bad*, *miss*, *suspect* and *good*) and readability characteristics conditional on the level of earnings management practices, I estimate the following cross-sectional model to test my second hypothesis:

$$Fog_{it} = \beta_0 + \beta_1 bad + \beta_2 miss + \beta_3 posacc_{it} + \beta_4 suspect\_negacc_{it} + \beta_5 suspect\_posacc_{it} + \sum_{c=6}^{18} \beta_c controls_{it} + \varepsilon_{it} \quad (1.6)$$

In the model (1.6), the dependent variable, *bad*, *miss* and the controls variable are the same of model (1.5). The *posacc* is a dummy variable equal 1 if firm has positive values of discretionary accruals, and 0 otherwise; *suspect_negacc* is a dummy variable equal 1 for a year in which the company appears in the suspect good news subsample and have negative values of discretionary accruals, and 0 otherwise; *suspect_posacc* is a dummy variable equal 1 for a year in which the company appears in the suspect good news subsample and have positive values of discretionary accruals, and 0 otherwise.

The β_3 coefficient represents the readability incremental effect (Fog) of firms with positive discretionary accruals on good news subsample. The β_4 coefficient represents the readability incremental effect (Fog) of firms with suspect good news subsample and negative values of discretionary accruals on good news subsample. Finally, the β_5 coefficient represents the readability incremental effect (Fog) of firms with suspect good news subsample and positive values of discretionary accruals on good news subsample. As predicted on my second hypothesis I expect that that β_5

be greater than β_4, because in this situation managers would be inflating their earnings to meet the last earnings benchmark.

Finally, the last analysis is to investigate whether the low readability of MD&A section, related to firms with suspect good news, is increasing in the level of earnings management practices. Therefore, to test my third hypothesis I estimate the following cross-sectional model:

$$Fog_{it} = \beta_0 + \beta_1 bad + \beta_2 miss + \beta_3 posacc_{it} + \beta_4 suspect\_negacc_{it} + \beta_5 suspect\_posacc\_low_{it} + \beta_6 suspect\_posacc\_high_{it} + \sum_{c=7}^{19} \beta_c controls_{it} + \varepsilon_{it} \quad (1.7)$$

The model (1.7) is very similar to the model (1.6) with one single modification. The subsample composed by firm with suspect good news to communicate to market and with high probability to beat or meet the earnings benchmark by earnings management practices (*suspect_posacc*) is segregated in two new subsamples. I calculated the median of discretionary accruals of *suspect_posacc* subsample and then I divide the observations in two subsamples, one below the median (*suspect_posacc_low*) and another above the median (*suspect_posacc_high*). The β_5 coefficient represents the readability incremental effect (Fog) of firms with suspect good news and positive values of discretionary accruals, but below from abnormal accruals median, on good news subsample. The β_6 coefficient represents the readability incremental effect (Fog) of firms with suspect good news and positive values of discretionary accruals, but above from abnormal accruals median, on good news subsample.

As predicted on my third hypothesis I expect that β_6 coefficient be great than β_5 coefficient. If this evidence is confirmed is an additional signal that earnings management in fact influence the readability level of MD&A section, showing that as

higher is the discretionary accruals of firms with suspect good news and with high probability to beat or met the earnings benchmark by earnings management practices worse will be the readability level of their MD&A section.

1.4 RESULTS

1.4.1 Distribution

The distribution of earnings change variable (*ue_eps_int*) is represents by the histogram on Fig 1. The histogram interval is one unit (cent) for range -50 to +50. The figure shows a single-peaked, bell-shaped distribution with a discontinuity around the zero point. This evidence is consistent with earnings management practices to avoid earnings decrease (BURGSTAHLER and DICHEV, 1997).

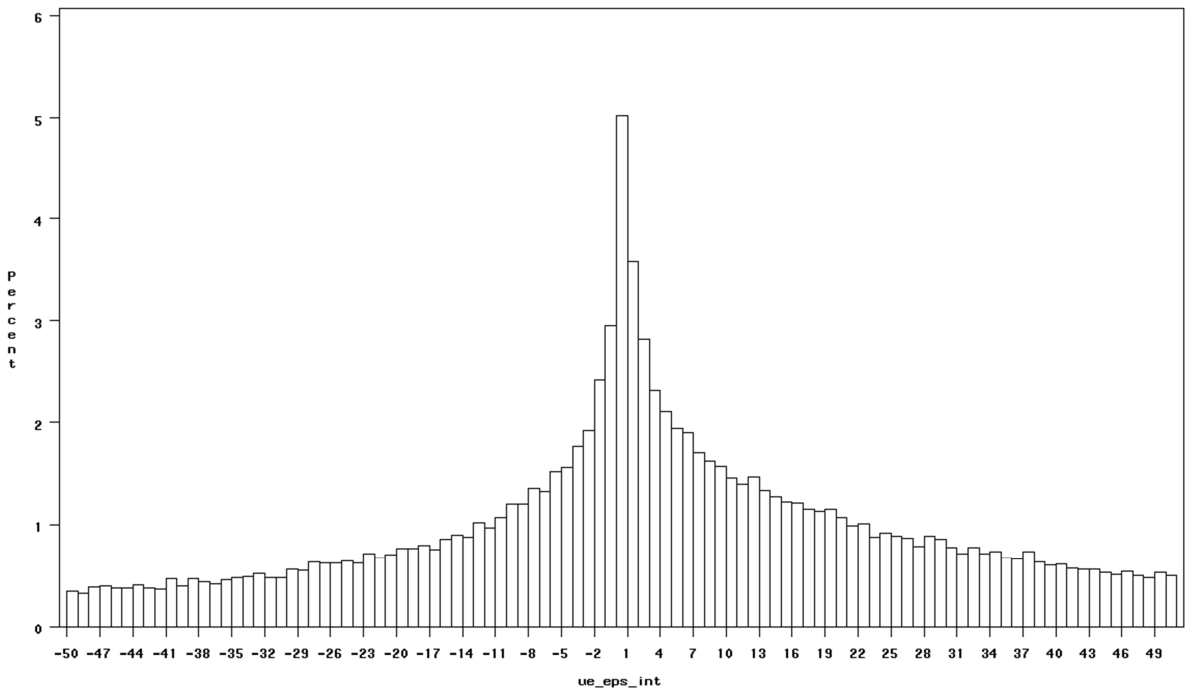

Figure 1. Empirical distribution of change in annual earnings per share before extraordinary items (Compustat item #*epspx*). The distribution interval is one unit (cent) for range -50 to +50. The percent of the number of observations in each earnings change interval is represented by the vertical axis.

1.4.2 Descriptive Statistics and Correlations

Table 2 presents descriptive statistics for the final sample. The mean Fog of the MD&A section is 18.02 and very similar to the value calculated by Li (2008) as well as the control variables. The unexpected earnings are on average close to zero with a mean of five cents. This result could be view jointly with the distribution analysis, as the first evidence that firms have incentive to keep their current year earnings close to last earnings. In other words, last year-earnings is an important benchmark observed by managers.

TABLE 2: DESCRIPTIVE STATISTICS

Variable	N	Mean	SD	Q1	Median	Q3
FOG	26967	18.020	1.613	16.880	17.907	19.048
UE_EPS	26967	0.049	40.521	-0.390	0.060	0.460
SIZE	26967	5.768	2.058	4.292	5.774	7.156
MTB	26967	1.999	1.757	1.100	1.496	2.242
AGE	26967	15.576	11.853	6.000	12.000	22.000
SI	26967	-0.032	0.248	-0.016	-0.001	0.000
EARN_VOL	26967	0.063	1.045	0.001	0.002	0.010
RET_VOL	26967	0.158	0.099	0.090	0.131	0.194
NBSEG	26967	1.032	0.531	0.693	0.693	1.386
NGSEG	26967	1.057	0.647	0.693	1.099	1.609
NITEMS	26967	278.878	29.838	255.000	283.000	301.000
MA	26967	0.398	0.489	0.000	0.000	1.000
SEO	26967	0.061	0.239	0.000	0.000	0.000
DLW	26967	0.653	0.476	0.000	1.000	1.000

Variable definitions: *FOG* is the Fog index calculated as (word per sentence + percent of complex words)*0.4; *UE_EPS* is the unexpected earnigs per share, calculated as the diference between current year earnings per share and last year earnings per share; *SIZE* is the logarithm of the market value of equity at the end of the fiscal year; *MTB* is the market-to-book calculated as the market value of equity plus book value of liability and divided by the book value of total assets at the end of the fiscal year; *AGE* is the number of years since a firm's first appearance in the CRSP monthly stock return files; *SI* is the amount of special item scaled by book value of assets; *RET_VOL*is the return volatility calculated as the standard deviation of the monthly stock returns in the prior year; *EARN_VOL* is the earnings volatility calculated as the standard deviation of the operating earnings during the prior five fiscal years; *NBSEG*is the logarithm of the number of business segments; *NGSEG* is the logarithm of the number of geographic segments; *NITEMS* is the logarithm of the number of non-missing items in Compustat; *MA* is a merged-and-acquisition dummy equals 1 for a year in which a company appears in the SDC Platinum M&A dataset as an acquirer

and 0 otherwise; *SEO* is a seasoned equity offering dummy equals 1 for a year in which company has a common equity offering in the secondary market according to the SDC Global New Issues database and 0 otherwise; *DL*is Delaware incorporation (DL) dummy equals 1 if firm is incorporated in Delaware and 0 otherwise.

Table 3 present the sample correlations. There is a significant and positive correlation between Fog index and market-to-book with a Pearson correlation coefficient of 0.115 and with a Spearman correlation coefficient 0.085. In other words, growth firms (firms with higher MTB ratio) have on average MD&A sections less readable. Bigger firms tend to have a MD&A section more readable, as evidenced by the Pearson correlation coefficient of -0.096, although the Spearman correlation coefficient is not statistically significant.

1.4.3 News Type and Readability Results

Table (4) presents the results of penny effect analysis. As Li (2008), I include year and industry fixed effects as potential determinants of the readability and the standard errors are clustered at the Fama-French 48 industry level once readability of MD&A section is likely to be correlated within industries. The same procedure is used on all next analyses.

As I predicted the coefficients which are statistically significant are concentrate around the last-earnings benchmark. Only firms that missed the last-earnings benchmark by one or two cents have MD&A section less readability than firms with good news. After two cents the penny effect is dissipated and no more observed. On the other hand, firms which beat or meet last-earnings benchmark by zero to four cents have on average MD&A section with higher readability level than firms with good news.

TABLE 3: PEARSON (UPPER TRIANGLE) AND SPEARMAN (LOWER TRIANGLE) CORRELATIONS

Variable	*FOG*	*UE_EPS*	*SIZE*	*MTB*	*AGE*	*SI*	*EARN VOL*	*RET VOL*	*NBSEG*	*NGSEG*	*NITEMS*	*MA*	*SEO*	*DLW*
FOG	1	0.001	**-0.096**	**0.115**	**-0.016**	**-0.024**	**0.035**	**0.103**	**-0.022**	**-0.090**	0.007	**-0.031**	-0.006	**0.062**
UE_EPS	-0.004	1	0.008	0.002	0.002	0.009	0.000	-0.004	0.004	-0.003	-0.005	0.001	0.001	0.002
SIZE	-0.111	**0.105**	1	**0.172**	**0.292**	**0.084**	**-0.049**	**-0.401**	**0.128**	**0.258**	**0.281**	**0.340**	**0.068**	**0.082**
MTB	**0.085**	**0.150**	**0.380**	1	**-0.123**	-0.012	**0.177**	**0.084**	**-0.110**	**-0.062**	-0.010	**-0.039**	**0.069**	**0.071**
AGE	**-0.017**	**0.019**	**0.237**	**-0.081**	1	**0.056**	**-0.029**	**-0.285**	**0.200**	**0.158**	**0.226**	**0.087**	**-0.088**	**-0.202**
SI	**-0.015**	**0.273**	0.008	**0.103**	**0.051**	1	-0.003	**-0.115**	0.008	0.008	0.007	-0.002	0.014	**-0.020**
EARN_VOL	**0.186**	**0.043**	**-0.376**	**0.201**	**-0.246**	**-0.021**	1	**0.061**	**-0.026**	**-0.033**	-0.009	-0.012	0.008	**0.017**
RET_VOL	**0.099**	**-0.040**	**-0.441**	**-0.079**	**-0.328**	**-0.126**	**0.431**	1	**-0.099**	**-0.093**	**-0.214**	**-0.177**	**0.066**	**0.063**
NBSEG	**-0.036**	0.006	**0.134**	**-0.102**	**0.189**	**-0.041**	**-0.186**	**-0.122**	1	**0.139**	**0.023**	**0.113**	**-0.033**	**-0.045**
NGSEG	**-0.083**	**0.018**	**0.265**	**0.027**	**0.145**	**-0.112**	**-0.094**	**-0.088**	**0.141**	1	**0.198**	**0.139**	**-0.043**	**0.019**
NITEMS	0.004	**0.022**	**0.268**	**0.048**	**0.229**	**-0.108**	**-0.126**	**-0.193**	**0.027**	**0.202**	1	**0.081**	0.012	**0.034**
MA	**-0.032**	**-0.016**	**0.338**	**0.050**	**0.068**	**-0.063**	**-0.187**	**-0.200**	**0.117**	**0.144**	**0.080**	1	-0.002	**0.027**
SEO	-0.005	**0.036**	**0.078**	**0.095**	**-0.101**	**0.018**	**0.051**	**0.068**	**-0.035**	**-0.043**	0.012	-0.002	1	**0.056**
DLW	**0.067**	**0.017**	**0.082**	**0.083**	**-0.214**	**-0.039**	**0.095**	**0.073**	**-0.050**	**0.025**	**0.036**	**0.027**	**0.056**	1

Variable definitions: *FOG* is the Fog index calculated as (word per sentence + percent of complex words)*0.4; *UE_EPS* is the unexpected earnings per share, calculated as the difference between current year earnings per share and last year earnings per share; *SIZE* is the logarithm of the market value of equity at the end of the fiscal year; *MTB* is the market-to-book calculated as the market value of equity plus book value of liability and divided by the book value of total assets at the end of the fiscal year; *AGE* is the number of years since a firm's first appearance in the CRSP monthly stock return files; *SI* is the amount of special item scaled by book value of assets; *RET_VOL* is the return volatility calculated as the standard deviation of the monthly stock returns in the prior year; *EARN_VOL* is the earnings volatility calculated as the standard deviation of the operating earnings during the prior five fiscal years; *NBSEG* is the logarithm of the number of business segments; *NGSEG* is the logarithm of the number of geographic segments; *NITEMS* is the logarithm of the number of non-missing items in Compustat; *MA* is a merged-and-acquisition dummy equals 1 for a year in which a company appears in the SDC Platinum M&A dataset as an acquirer and 0 otherwise; *SEO* is a seasoned equity offering dummy equals 1 for a year in which company has a common equity offering in the secondary market according to the SDC Global New Issues database and 0 otherwise; *DL* is Delaware incorporation (DL) dummy equals 1 if firm is incorporated in Delaware and 0 otherwise. Bolded coefficients are statistically significant ate the 0.01 level.

Actually, after the third cent the penny effect reduces from 0.255 to 0.186. Therefore, after four cents the penny effect is dissipated and no more observed, after three cents the effect loses magnitude

The control variables indicate that growth firms, older firms, firms with more volatile return and firms incorporated in Delaware have more complex MD&A section, as evidenced by the positive and significant coefficients on *MTB, AGE, RET_VOL* and *DLW*. On the other hand, larger firms and firms with a seasoned equity offering have less complex MD&A section, as evidenced by the negative and significant coefficients on *SIZE* and *SEO*. The other variables as *SI, EARN_VOL, NBSEG, NITEMS* and *MA* present coefficients do not statistically different from zero. Although, some results are counter intuitive as larger firms have less complex MD&A readability all the results related with control variables is quite similar to Li's (2008) results.

Taken together, results indicate that around the last-earnings benchmark there is an unusual behavior of the readability level. Firms closer to zero change in earnings have MD&A section less readable than firms more distant from zero change in earnings.

Table 5 presents the estimate results from regressing readability proxies on type of news. Column [a], *bad* is defined as all firms below minus one cent, *miss* is all firms which miss the benchmark by one cent, *suspect* is all firms which beat or meet the benchmark by zero to one cent, and *good* (the control group) is all firms above one cent. Column [b] *bad* is defined as all firms below minus two cents, *miss* is all firms which miss the benchmark by one to two cents, *suspect* is all firms which beat or meet the benchmark by zero to two cents, and *good* (the control group) is all firms above two cents. Column [c] *bad* is defined as all firms below minus three cents, *miss* is all firms which miss the benchmark by one to three cents, *suspect* is all firms which

beat or meet the benchmark by zero to three cents, and *good* (the control group) is all firms above three cents. This presentation in three columns is also utilized on the next analyses.

TABLE 4: PENNY EFFECT AND READABILITY

Independent Variable	Pred. Sign	FOG		
		Coefficient	t-stat	
Intecept		19.672	38.08	***
BAD	+	0.063	2.84	***
MISS_7	+	-0.071	-0.64	
MISS_6	+	0.107	1.22	
MISS_5	+	-0.068	-0.59	
MISS_4	+	0.059	0.56	
MISS_3	+	0.065	0.93	
MISS_2	+	0.232	2.19	**
MISS_1	+	0.318	3.32	***
MAKE_0	+	0.134	1.86	*
MAKE_1	+	0.246	2.44	**
MAKE_2	+	0.248	2.38	**
MAKE_3	+	0.255	2.53	**
MAKE_4	+	0.186	2.20	**
MAKE_5	+	0.164	1.45	
MAKE_6	+	0.101	1.15	
MAKE_7	+	0.119	1.15	
SIZE	+	-0.068	-3.21	***
MTB	+	0.062	5.12	***
AGE	-	0.014	6.40	***
SI	-	-0.030	-1.22	
EARN_VOL	+	0.004	0.32	
RET_VOL	+	0.931	5.88	***
NBSEG	+	0.046	1.27	
NGSEG	+	-0.168	-3.52	***
NITEMS	+	-0.002	-1.33	
MA	+	0.034	1.17	
SEO	+	-0.185	-3.63	***
DLW	_+/-	0.177	3.77	***
Controls		Yes		
Year Dummies		Yes		

continue

Industry Dummies	Yes
Observations	26967
R-squared	0.1211

Variable definitions: *BAD* is a dummy variable equals 1 if the change in earnings per share before extraordinary items (EPS) is less than -0.07, and 0 otherwise; *MISS_7* is a dummy variable equals 1 if the change in EPS equals -7, and zero otherwise; *MISS_6* is a dummy variable equals 1 if the change in EPS equals -6, and zero otherwise; *MISS_5* is a dummy variable equals 1 if the change in EPS equals -5, and zero otherwise; *MISS_4* is a dummy variable equals 1 if the change in EPS equals -4, and zero otherwise; *MISS_3* is a dummy variable equals 1 if the change in EPS equals -3, and zero otherwise; *MISS_2* is a dummy variable equals 1 if the change in EPS equals -2, and zero otherwise; *MISS_1* is a dummy variable equals 1 if the change in EPS equals -1, and zero otherwise; *MAKE_0* is a dummy variable equals 1 if the change in EPS equals 0, and zero otherwise; *MAKE_1* is a dummy variable equals 1 if the change in EPS equals 1, and zero otherwise; *MAKE_2* is a dummy variable equals 1 if the change in EPS equals 2, and zero otherwise; *MAKE_3* is a dummy variable equals 1 if the change in EPS equals 3, and zero otherwise; *MAKE_4* is a dummy variable equals 1 if the change in EPS equals 4, and zero otherwise; *MAKE_5* is a dummy variable equals 1 if the change in EPS equals 5, and zero otherwise; *MAKE_6* is a dummy variable equals 1 if the change in EPS equals 6, and zero otherwise; *MAKE_7* is a dummy variable equals 1 if the change in EPS equals 7, and zero otherwise; *FOG* is the Fog index calculated as (word per sentence + percent of complex words)*0.4; *SIZE* is the logarithm of the market value of equity at the end of the fiscal year; *MTB* is the market-to-book calculated as the market value of equity plus book value of liability and divided by the book value of total assets at the end of the fiscal year; *AGE* is the number of years since a firm's first appearance in the CRSP monthly stock return files; *SI* is the amount of special item scaled by book value of assets; *RET_VOL* is the return volatility calculated as the standard deviation of the monthly stock returns in the prior year; *EARN_VOL* is the earnings volatility calculated as the standard deviation of the operating earnings during the prior five fiscal years; *NBSEG* is the logarithm of the number of business segments; *NGSEG* is the logarithm of the number of geographic segments; *NITEMS* is the logarithm of the number of non-missing items in Compustat; *MA* is a merged-and-acquisition dummy equals 1 for a year in which a company appears in the SDC Platinum M&A dataset as an acquirer and 0 otherwise; *SEO* is a seasoned equity offering dummy equals 1 for a year in which company has a common equity offering in the secondary market according to the SDC Global New Issues database and 0 otherwise; *DL* is Delaware incorporation (DL) dummy equals 1 if firm is incorporated in Delaware and 0 otherwise.
t-statistics are based on standard errors clustered at the Fama-French 48 industry level.
***/**/* means significance at 0.01, 0.05 and 0.10 level, respectively.

As predicted on my first hypothesis I find that firms with bad news, firms which just missed earnings benchmark and firms with suspect good news present MD&A section less readable than firms with good news to communicate to market, in most

case all the coefficients are statistically significant at least 5 percent. Additionally, the just miss earnings benchmark subsample also has MD&A section less readable than bad news subsample. The test 1 presents the F-statistics for the three approaches and in all cases the difference is statistically significant at least 5 percent. This evidence suggest that firms which missed the earnings benchmark by some pennies have more incentive to complicate the readability level of MD&A section once the market can interpret as evidence of hidden problems at the firm (GRAHAM et al 2005).

Firms with suspect good news also have MD&A section less readable than bad news subsample. The test 2 presents the F-statistics for the three approaches and in most cases the difference is statistically significant at least 5 percent. In particular, this evidence suggests that the alternative explanation mentioned by Bloomfield (2008) which the level of readability could be attributed to the difficulty of explaining unusual bad events and for this reason bad news are more difficult to explain than good news is not necessary true.

The results suggest that even “good news” is difficult to communicate to market and perhaps could be another reason to explain the readability level around last-earnings benchmark, perhaps related to managers’ discretion and not just by the type of news. Taken together, the results indicate that type of news influences the readability level of MD&A section and there is an unusual behavior of the readability level around last earnings benchmark.

TABLE 5: RELATION BETWEEN TYPE OF NEWS AND READABILITY

Independent Variable	Pred. Sign	[a] FOG [0.01]			[b] FOG [0.01 to 0.02]			[c] FOG [0.01 to 0.03]		
		Coefficient	t-stat		Coefficient	t-stat		Coefficient	t-stat	
Intercept		19.724	38.51	***	19.708	38.52	***	19.700	38.50	***
BAD	+	0.045	2.15	**	0.046	2.11	**	0.049	2.20	**
MISS	+	0.298	3.17	***	0.256	3.24	***	0.193	3.20	***
SUSPECT	+	0.169	2.32	**	0.195	3.34	***	0.210	3.79	***
SIZE	+	-0.070	-3.27	***	-0.069	-3.24	***	-0.069	-3.22	***
MTB	+	0.064	5.19	***	0.063	5.15	***	0.063	5.17	***
AGE	-	0.014	6.36	***	0.014	6.35	***	0.014	6.38	***
SI	-	-0.030	-1.21		-0.031	-1.24		-0.032	-1.24	
EARN_VOL	+	0.004	0.35		0.004	0.37		0.004	0.40	
RET_VOL	+	0.913	5.69	***	0.916	5.72	***	0.922	5.77	***
NBSEG	+	0.046	1.27		0.046	1.26		0.046	1.27	
NGSEG	+	-0.170	-3.56	***	-0.169	-3.55	***	-0.169	-3.55	***
NITEMS	+	-0.002	-1.37		-0.002	-1.35		-0.002	-1.34	
MA	+	0.036	1.21		0.035	1.21		0.035	1.21	
SEO	+	-0.186	-3.72	***	-0.186	-3.68	***	-0.185	-3.65	***
DLW	_+/-	0.177	3.77	***	0.177	3.76	***	0.177	3.76	***
Year Dummies		Yes			Yes			Yes		
Industry Dummies		Yes			Yes			Yes		
Observations		26967			26967			26967		
R-squared		0.1203			0.1205			0.1206		

continue

Test on coefficients:	F-statistics		F-statistics		F-statistics	
Test 1: *MISS* - *BAD* = 0	6.37	***	5.88	**	4.17	**
Test 2: *SUSPECT* - *BAD* = 0	2.99	*	6.19	**	8.23	***

Variable defitions: *BAD* is a dummy variable equals 1 if the change in earnings per share before extraordinary items (EPS) is less than -0.01 (Column 1), less than -0.02 (Column 2), less than -0.03 (Column 3); *MISS* is a dummy variable equals 1 if the change in EPS is -0.01 <= EPS < 0 (Column 1), -0.02 <= EPS < 0 (Column 2), -0.03 <= EPS < 0 (Column 3); *SUSPECT* is a dummy variable equals 1 if the change in EPS is 0 <= EPS < 0.01 (Column 1), 0 <= EPS < 0.02 (Column 2), 0 <= EPS < 0.03 (Column 3); *FOG* is the Fog index calculated as (word per sentence + percent of complex words)*0.4; *SIZE* is the logarithm of the market value of equity at the end of the fiscal year; *MTB* is the market-to-book calculated as the market value of equity plus book value of liability and divided by the book value of total assets at the end of the fiscal year; *AGE* is the number of years since a firm's first appearance in the CRSP monthly stock return files; *SI* is the amount of special item scaled by book value of assets; *RET_VOL* is the return volatility calculated as the standard deviation of the monthly stock returns in the prior year; *EARN_VOL* is the earnings volatility calculated as the standard deviation of the operating earnings during the prior five fiscal years; *NBSEG* is the logarithm of the number of business segments; *NGSEG* is the logarithm of the number of geographic segments; *NItems* is the logarithm of the number of non-missing items in Compustat; *MA* is a merged-and-acquisition dummy equals 1 for a year in which a company appears in the SDC Platinum M&A dataset as an acquirer and 0 otherwise; *SEO* is a seasoned equity offering dummy equals 1 for a year in which company has a common equity offering in the secondary market according to the SDC Global New Issues database and 0 otherwise; *DL* is Delaware incorporation (DL) dummy equals 1 if firm is incorporated in Delaware and 0 otherwise.

t-statistics are based on standard errors clustered at the Fama-French 48 industry level.

***/**/* means significance at 0.01, 0.05 and 0.10 level, respectively.

1.4.4 Earnings Management and Readability Results

Table 6 presents the estimated results of earnings management proxies. Panel A provides the estimated coefficient of the normal level accruals. The equations are estimated cross-sectionally for each industry-year with at least 15 observations and for all firms with information available on Compustat to calculate each model between fiscal years 1992 to 2013.

Panel A shows the coefficients estimated by Jones (1991) model and Dechow et al. (1995) model. To calculate the discretionary accruals by Kothari (2005) model I use the Jones (1991) as base. The coefficients for each model are the mean values of the coefficients across industry-year. All the reported coefficients are statistically significant and similar to those provide in prior studies (ZANG, 2012, KOTHARI et al., 2005). Panel B provides summary statistics for earnings management proxies.

TABLE 6: MENSUREMENT OF EARNINGS MANAGEMENT PROXIES

Panel A: Estimation of the Discretionary Accruals

	Jones (1991)		Dechow et al. (1995)	
Variable	Coefficient		Coefficient	
1/AT$_{t-1}$	-1.1753	***	-1.1776	***
ΔREV$_t$	-0.0577	***		
(ΔREV$_t$ - ΔREC$_t$)			0.5756	***
PPE$_t$	-0.0232	***	-0.1991	***

Panel B: Summary statistics for earnings management proxies

Variable	N	Mean	SD	Q1	Median	Q3
Jones (1991)	73907	0.000	58.822	-0.154	0.039	0.346
Dechow et al. (1995)	73907	0.000	58.683	-0.160	0.037	0.335
Kothari et al. (2005)	63010	-0.101	75.775	-0.254	0.000	0.258

Variables definitions: *AT* is equal total assets; *ΔREV* is equal to change in revenue; *ΔREC* is equal to change in receivables; *PPE* is equal to plant, properties and equipament.

***/**/* means significance at 0.01, 0.05 and 0.10 level, respectively.

Table 7 presents the estimate results from regressing readability proxy (*FOG*) on type of news conditional on the level of earnings management. As in previous analyses, in column [a], *bad* is defined as all firms below minus one cent, *miss* is all firms which miss the benchmark by one cent, *suspect_negacc* is all firms which beat or meet the benchmark by zero to one cent and have negative discretionary accruals, *suspect_posacc* is all firms which beat or meet the benchmark by zero to one cent and have positive discretionary accruals, and *good* (the control group) is all firms above one cent. Column [b] *bad* is defined as all firms below minus two cents, *miss* is all firms which miss the benchmark by one to two cents, *suspect_negacc* is all firms which beat or meet the benchmark by zero to two cents and have negative discretionary accruals, *suspect_posacc* is all firms which beat or meet the benchmark by zero to two cents and have positive discretionary accruals, and *good* (the control group) is all firms above two cents. Column [c] *bad* is defined as all firms below minus three cents, *miss* is all firms which miss the benchmark by one to three cents, *suspect_negacc* is all firms which beat or meet the benchmark by zero to three cents and have negative discretionary accruals, *suspect_posacc* is all firms which beat or meet the benchmark by zero to three cents and have positive discretionary accruals, and *good* (the control group) is all firms above three cents. Panel A shows results based on Jones (1991) model, panel B and panel C presents robustness test results based on Dechow et al. (1995) model and Kothari et al. (2005) model, respectively.

As presented in Panel A the *suspect_negacc* group coefficients are not statistically different from zero. In other words, there is no difference between suspect firms with low probability to beat or meet the last earnings benchmark with firm which have good news to communicate to market. On the other hand, the *suspect_posacc* group presents coefficients positive and statistically different from zero at 1 percent. It

means that suspect firms with high probability to beat or meet the last earnings benchmark have MD&A section less readable than firms with good news to communicate to market. On robustness tests, Dehow et al. (1995) and Kothari et al. (2005), results are quite similar.

As predicted on my second hypothesis, I find that firms with suspect good news and with high probability to beat or meet last year earnings per share through earnings management methods have annual report (MD&A) less readable than firms with suspect good news with low probability, in the most of cases at 10 percent of significance (F-statistics) for Jones (1991) model. Based on robustness test results the results are confirmed just for Dechow et al. (1995) model in column [1] when the *suspect* group is defined as all firms which beat or meet the benchmark by zero to one cent. The results are not statistically confirmed by Kothari et al. (2005) model.

In general, the results suggest that managers that engage in earnings management practices to beat or meet the last year earnings benchmark also use strategic corporate disclosure activities in order to hide the path taken to achieve their goals. More specifically, they write a less readable MD&A section.

As an additional and sensitive analysis I perform a test to identify whether the earnings management effect is increasing on the readability level of MD&A section of suspect firms with high probability to beat or meet the last earnings benchmark through earnings management practices. Table 8 presents the estimate results from this analysis. As predicted on my third hypothesis I find the effect is increasing. Panel A shows that both coefficients, *suspect_posacc_low* and *suspect_posacc_high* are positive and statistically different from zero.

TABLE 7: RELATION BETWEEN TYPE OF NEWS AND READABILITY CONDITIONAL ON THE LEVEL OF EARNINGS MANAGEMENT

Panel A: Jones (1991)		[a] FOG [0.01]		[b] FOG [0.01 to 0.02]		[c] FOG [0.01 to 0.03]	
Independent Variable	Pred. Sign	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept		19.623	36.36 ***	19.607	36.41 ***	19.597	36.40 ***
BAD	+	0.052	2.41 **	0.053	2.36 **	0.057	2.48 **
MISS	+	0.326	3.37 ***	0.266	3.31 ***	0.200	3.30 ***
POSACC		0.009	0.31	0.009	0.31	0.008	0.28
SUSPECT_negacc	+	-0.042	-0.31	0.067	0.58	0.102	1.02
SUSPECT_posacc	+	0.336	3.57 ***	0.302	4.93 ***	0.300	5.26 ***
Control Variables		Yes		Yes		Yes	
Year Dummies		Yes		Yes		Yes	
Industry Dummies		Yes		Yes		Yes	
Observations		26143		26143		26143	
R-squared		0.1206		0.1207		0.1208	
Test on coefficients:			F-statistics		F-statistics		F-statistics
Test 3: *SUSPECT_negacc* - *SUSPECT_posacc* = 0			5.71 **		3.06 *		3.00 *

continue

Panel B: Dechow et al. (1995)		[a] FOG [0.01]		[b] FOG [0.01 to 0.02]		[c] FOG [0.01 to 0.03]	
Independent Variable	Pred. Sign	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Intercept		19.620	36.15 ***	19.604	36.20 ***	19.594	36.17 ***
BAD	+	0.052	2.43 **	0.053	2.39 **	0.057	2.50 **
MISS	+	0.327	3.37 ***	0.266	3.31 ***	0.200	3.30 ***
POSACC		0.013	0.50	0.014	0.53	0.013	0.48
SUSPECT_negacc	+	0.002	0.02	0.117	1.08	0.126	1.36
SUSPECT_posacc	+	0.313	3.58 ***	0.272	5.28 ***	0.290	4.91 ***
Control Variables		Yes		Yes		Yes	
Year Dummies		Yes		Yes		Yes	
Industry Dummies		Yes		Yes		Yes	
Observations		26143		26143		26143	
R-squared		0.1205		0.1206		0.1208	
Test on coefficients:			F-statistics		F-statistics		F-statistics
Test 3*: *SUSPECT_negacc* - *SUSPECT_posacc* = 0			4.33 **		1.75		2.39

continue

Panel C: Kothari (2005)		[a] FOG [0.01]			[b] FOG [0.01 to 0.02]			[c] FOG [0.01 to 0.03]		
Independent Variable	Pred. Sign	Coefficient	t-stat		Coefficient	t-stat		Coefficient	t-stat	
Intercept		19.565	36.27	***	19.548	36.26	***	19.539	36.25	***
BAD	+	0.053	2.40	**	0.054	2.33	**	0.058	2.42	**
MISS	+	0.324	3.37	***	0.265	3.32	***	0.199	3.29	***
POSACC		0.008	0.27		0.009	0.28		0.008	0.25	
SUSPECT_negacc	+	0.178	1.61		0.195	2.12	**	0.199	2.41	**
SUSPECT_posacc	+	0.187	2.06	**	0.201	2.87	***	0.232	3.83	***
Control Variables		Yes			Yes			Yes		
Year Dummies		Yes			Yes			Yes		
Industry Dummies		Yes			Yes			Yes		
Observations		26038			26038			26038		
R-squared		0.121			0.1212			0.1214		

Test on coefficients:	F-statistics	F-statistics	F-statistics
Test 3*: *SUSPECT_negacc* - *SUSPECT_posacc* = 0	0	0	0.11

Variable defitions: *BAD* is a dummy variable equals 1 if the change in earnings per share before extraordinary items (EPS) is less than -0.01 (Column 1), less than -0.02 (Column 2), less than -0.03 (Column 3); *MISS* is a dummy variable equals 1 if the change in EPS is -0.01 <= EPS < 0 (Column 1), -0.02 <= EPS < 0 (Column 2), -0.03 <= EPS < 0 (Column 3); *POSACC* is a dummy variable equals 1 if firm presentes positive discretionary accruals; *SUSPECT_negacc* is a dummy variable equals 1 if the change in EPS is 0 <= EPS < 0.01 (Column 1), 0 <= EPS < 0.02 (Column 2), 0 <= EPS < 0.03 (Column 3) and firm presents negative discretionary accruals; *SUSPECT_posacc* is a dummy variable equals 1 if 0 <= EPS < 0.01 (Column 1), 0 <= EPS < 0.02 (Column 2), 0 <= EPS < 0.03 (Column 3) and positive discretionary accruals; *FOG* is the Fog index calculated as (word per sentence + percent of complex words)*0.4; *SIZE* is the logarithm of the market value of equity at the end of the fiscal year; *MTB* is the market-to-book calculated

as the market value of equity plus book value of liability and divided by the book value of total assets at the end of the fiscal year; *AGE* is the number of years since a firm's first appearance in the CRSP monthly stock return files; *SI* is the amount of special item scaled by book value of assets; *RET_VOL* is the return volatility calculated as the standard deviation of the monthly stock returns in the prior year; *EARN_VOL* is the earnings volatility calculated as the standard deviation of the operating earnings during the prior five fiscal years; *NBSEG* is the logarithm of the number of business segments; *NGSEG* is the logarithm of the number of geographic segments; *NItems* is the logarithm of the number of non-missing items in Compustat; *MA* is a merged-and-acquisition dummy equals 1 for a year in which a company appears in the SDC Platinum M&A dataset as an acquirer and 0 otherwise; *SEO* is a seasoned equity offering dummy equals 1 for a year in which company has a common equity offering in the secondary market according to the SDC Global New Issues database and 0 otherwise; *DL* is Delaware incorporation (DL) dummy equals 1 if firm is incorporated in Delaware and 0 otherwise.

Control variables are omitted just for presentation proposal.

t-statistics are based on standard errors clustered at the Fama-French 48 industy level.

***/**/* means significance at 0.01, 0.05 and 0.10 level, respectively.

As present by F-test the coefficients between these two groups are in the most case different at least 5 percent. Moreover, suspect firms with high probability to beat or meet the last earnings benchmark through earnings management and above the median of discretionary accruals have an effect two times greater than similar firms, but below the median of discretionary accruals.

These results are confirmed by the robustness tests. Panel [c] shows, based on Kothari et al. (2005) model, the effect is greater than the effect calculated by Jones (1991) model. Based on Kothari et al. (2005) suspect firms with high probability to beat or meet the last earnings benchmark through earnings management and above the median of discretionary accruals have an effect six times greater than similar firms, but below the median of discretionary accruals.

1.5 CONCLUSION

This paper provides evidence that firms which engaging in earnings management practices to meet or beat the last-earnings benchmark, use strategic corporate disclosure activities in order to hide the path taken to achieve their goals. Results suggest that firms with high probability to manage their earnings to meet or beat the last earnings benchmark have on average MD&A section of annual report less readable than firms which have low probability to manage earnings and even than firms with good or bad news to communicate to market.

Different analyses are applied to show that managers use some discretion on the readability of MD&A section. First, I identified an unusual behavior of readability level around the last-year earnings benchmark.

TABLE 8: RELATION BETWEEN TYPE OF NEWS AND READABILITY CONDITIONAL ON THE LEVEL OF EARNINGS MANAGEMENT - INCRESING ANALYSIS

Panel A: Jones (1991)		[a] FOG [0.01]			[b] FOG [0.01 to 0.02]			[c] FOG [0.01 to 0.03]		
Independent Variable	Pred. Sign	Coefficient	t-stat		Coefficient	t-stat		Coefficient	t-stat	
Intercept		19.622	36.32	***	19.605	36.40	***	19.593	36.35	***
BAD	+	0.052	2.41	**	0.053	2.36	**	0.057	2.47	**
MISS	+	0.326	3.37	***	0.266	3.32	***	0.200	3.30	***
POSACC		0.009	0.31		0.009	0.31		0.008	0.28	
SUSPECT_negacc		-0.042	-0.31		0.067	0.58		0.102	1.02	
SUSPECT_posacc_low	+	0.285	2.54	**	0.185	2.19	**	0.181	2.35	**
SUSPECT_posacc_high	+	0.386	2.71	***	0.418	5.16	***	0.420	4.88	***
Control Variables		Yes			Yes			Yes		
Year Dummies		Yes			Yes			Yes		
Industry Dummies		Yes			Yes			Yes		
Observations		26143			26143			26143		
R-squared		0.1207			0.1208			0.121		
Test on coefficients:		F-statistics			F-statistics			F-statistics		
Test 4: *SUSPECT_posEM_low* - *SUSPECT_posEM_high* = 0		0.40			5.51		**	6.89		**

continue

Panel B: Dechow et al. (1995)		[a] FOG [0.01]			[b] FOG [0.01 to 0.02]			[c] FOG [0.01 to 0.03]		
Independent Variable	Pred. Sign	Coefficient	t-stat		Coefficient	t-stat		Coefficient	t-stat	
Intercept		19.619	36.13	***	19.602	36.18	***	19.592	36.14	***
BAD	+	0.052	2.43	**	0.053	2.38	**	0.057	2.49	**
MISS	+	0.327	3.38	***	0.266	3.32	***	0.200	3.30	***
POSACC		0.013	0.50		0.014	0.54		0.013	0.48	
SUSPECT_negacc		0.002	0.02		0.117	1.08		0.126	1.36	
SUSPECT_posacc_low	+	0.269	2.28	**	0.169	2.30	**	0.186	2.31	**
SUSPECT_posacc_high	+	0.358	3.04	***	0.374	5.98	***	0.395	5.24	***
Control Variables		Yes			Yes			Yes		
Year Dummies		Yes			Yes			Yes		
Industry Dummies		Yes			Yes			Yes		
Observations		26143			26143			26143		
R-squared		0.1205			0.1208			0.1210		
Test on coefficients:		F-statistics			F-statistics			F-statistics		
Test 4*: *SUSPECT_posEM_low - SUSPECT_posEM_high* = 0		0.38			6.17		**	6.40		**

continue

Panel C: Kothari et al. (2005)		[a] FOG [0.01]			[b] FOG [0.01 to 0.02]			[c] FOG [0.01 to 0.03]		
Independent Variable	Pred. Sign	Coefficient	t-stat		Coefficient	t-stat		Coefficient	t-stat	
Intercept		19.569	36.25	***	19.552	36.22	***	19.544	36.24	***
BAD	+	0.053	2.40	**	0.054	2.32	**	0.058	2.41	**
MISS	+	0.324	3.37	***	0.266	3.32	***	0.200	3.29	***
POSACC		0.008	0.27		0.009	0.28		0.008	0.25	
SUSPECT_negacc		0.178	1.61		0.195	2.12	**	0.199	2.41	**
SUSPECT_posacc_low	+	0.067	0.62		0.053	0.41		0.060	0.59	
SUSPECT_posacc_high	+	0.308	2.11	**	0.349	4.59	***	0.403	5.98	***
Control Variables		Yes			Yes			Yes		
Year Dummies		Yes			Yes			Yes		
Industry Dummies		Yes			Yes			Yes		
Observations		26038								
R-squared		0.1211			0.1214			0.1216		
Test on coefficients:			F-statistics			F-statistics			F-statistics	
Test 4*: *SUSPECT_posEM_low* - *SUSPECT_posEM_high* = 0			2.13			3.74	*		8.31	***

Variable definitions: *BAD* is a dummy variable equals 1 if the change in earnings per share before extraordinary items (EPS) is less than -0.01 (Column 1), less than -0.02 (Column 2), less than -0.03 (Column 3); *MISS* is a dummy variable equals 1 if the change in EPS is -0.01 <= EPS < 0 (Column 1), -0.02 <= EPS < 0 (Column 2), -0.03 <= EPS < 0 (Column 3); *POSACC* is a dummy variable equals 1 if firm presents positive discretionary accruals; *SUSPECT_negacc* is a dummy variable equals 1 if the change in EPS is 0 <= EPS < 0.01 (Column 1), 0 <= EPS < 0.02 (Column 2), 0 <= EPS < 0.03 (Column 3) and firm presents negative discretionary accruals; *SUSPECT_posacc_low* is a dummy variable equals 1 if 0 <= EPS < 0.01 (Column 1), 0 <=

EPS < 0.02 (Column 2), 0 <= EPS < 0.03 (Column 3) and positive discretionary accruals and belw the median; *SUSPECT_posacc_high* is a dummy variable equals 1 if 0 <= EPS < 0.01 (Column 1), 0 <= EPS < 0.02 (Column 2), 0 <= EPS < 0.03 (Column 3) and positive discretionary accruals and above the median; *FOG* is the Fog index calculated as (word per sentence + percent of complex words)*0.4; *SIZE* is the logarithm of the market value of equity at the end of the fiscal year; *MTB* is the market-to-book calculated as the market value of equity plus book value of liability and divided by the book value of total assets at the end of the fiscal year; *AGE* is the number of years since a firm's first appearance in the CRSP monthly stock return files; *SI* is the amount of special item scaled by book value of assets; *RET_VOL* is the return volatility calculated as the standard deviation of the monthly stock returns in the prior year; *EARN_VOL* is the earnings volatility calculated as the standard deviation of the operating earnings during the prior five fiscal years; *NBSEG* is the logarithm of the number of business segments; *NGSEG* is the logarithm of the number of geographic segments; *NItems* is the logarithm of the number of non-missing items in Compustat; *MA* is a merged-and-acquisition dummy equals 1 for a year in which a company appears in the SDC Platinum M&A dataset as an acquirer and 0 otherwise; *SEO* is a seasoned equity offering dummy equals 1 for a year in which company has a common equity offering in the secondary market according to the SDC Global New Issues database and 0 otherwise; *DL* is Delaware incorporation (DL) dummy equals 1 if firm is incorporated in Delaware and 0 otherwise.
Control variables are omitted just for presentation proposal.
t-statistics are based on standard errors clustered at the Fama-French 48 industy level.
***/**/* means significance at 0.01, 0.05 and 0.10 level, respectively.

Around this benchmark firms have on average MD&A section less readable than firms which are more distant from this point. My results also show that firms that have suspect good news and that inflate earnings through earnings management practices present on average MD&A sections less readable than firms with similar news, but that don't engage in earnings management.

Additionally, my results also show evidence that the earnings management effect is increasing on the level of positive MD&A section readability. In other words, suspect firms which have higher level of discretionary accruals have on average MD&A section less readable than firm with lower level of positive discretionary accruals.

In addition, my results contest the alternative explanation proposed by Bloomfield (2008). According to Bloomfield (2008) the relation between poor performance and/or transitory earnings with less readable annual reports could be attributed to the difficulty of explaining these unusual events and not necessarily to the managers' discretion. My results do not indicate that the reason is just the type of news, but the reason is also relate to managers' discretion on the annual report readability to hide adverse information from investors.

The main contribution of this paper is to show that managers beyond to manage earnings they also engaging in the readability level of MD&A section in order to obfuscate adverse information to market. Therefore, firms with MD&A section harder to read can be view as a signal of earnings with poor quality. In terms of future research I suggest some extension ideas as to analyze whether managers' behavior related to readability can be observed with different managers' incentive, or different benchmark as well as different reports.

Chapter 2

2 DOES THE LEVEL OF READABILITY HELP TO PREDICT FINANCIAL MISREPORTING?

2.1 INTRODUCTION

Financial misreporting is a critical point to the efficient function of capital markets. In the last decades, investors' confidence in financial reporting system has been affected by the increase in the number of cases of accounting misstatements or accounting fraud such as well-know incidents involving Enron, WordCom and Tyco. A better understanding of that process is still a "big deal" for investor, financial analyst, auditor and regulators, especially if would be possible to predict when the financial misreporting will occur. Because the relevance of that issue to capital markets, some academic papers have addressed questions related to earnings misstatements and developed predicting models to identify suspicious firms (e.g. BENEISH, 1999; WILSON, 2008; DECHOW, GE, LARSON and SLOAN, 2011; LARCKER and ZAKOLYUKINA, 2012).

In this paper, I take a different approach to identify financial misreporting. Instead of using only financial variables such as accruals, assets quality index, leverage ratio etc. (e.g. BENEISH, 1997, DECHOW et al.1996), I use a textual analysis on annual mandatory report (10-K). Specifically, I analyze the readability level of Management Discussion and Analysis (MD&A) section, measured by Fog index from the computational linguistic literature. Based on the assumption that managers have an incentive to obfuscate information related to accounting problems or discretion decision as managing earnings, I conjecture that the readability level of financial reports can be used to identify material accounting misstatements.

In an extensive review of earnings quality, Dechow, Ge and Schrand (2010) present three external indicators of earnings misstatements, including the *Accounting and Auditing Enforcement Releases* (AAERs). The AAERs are issued by the U.S. Securities and Exchange Commission (SEC) at the conclusion of an investigation against firms, managers, auditors or other parties involved in violations of SEC and federal rules. Since 1982, the SEC already issued more than 3,000 AAERs, which represents more than 1,200 firm misstatement events.

Prior literature, using AAER database, provides evidence that the characteristics of a manipulating firm[2] are associated to: (i) the composition of board directors and CEOs (e.g., DECHOW et al., 1996; BEASLEY, 1996; FARBER; 2005); (ii) the likelihood to violate debt covenants (e.g. DECHOW et al., 1996; BENEISH, 1999); (iii) the need to raise financing at favorable prices (e.g. DECHOW et al., 1996; DECHOW et.al, 2011); (iv) financial characteristics as accruals quality, financial performance, nonfinancial measures (DECHOW et al. 2011); and (v) linguistic features of conference calls (LARCKER and ZAKOLYUKINA, 2012).

In recent years textual analysis has been used in accounting literature in different ways. Li (2011), in a comprehensive review, highlight some studies which applying textual analysis to analyze issues related to: (i) information content (e.g. LI and RAMESH, 2009; LI, 2010); (ii) market efficient (e.g. YOU and ZHANG, 2009; LI LUNDHOLM and MINNINS, 2013); (iii) litigation risk (e.g. ROGERS, BUSKIRK and ZECHMAN, 2011); and (iv) firms' information environment (MILLER, 2010; LEHAVI, LI and MERKLEY, 2011). Although prior literature shows wide documented evidence of AAERs firm characteristics and different application of textual analysis, there is no evidence related to the level of readability of a mandatory report such the 10-K to

[2] In this paper I use the term manipulating firm as a synonymous of misstating firm.

identify firms with higher probability to be subjected to a SEC investigation. Therefore this paper feels this gap in the literature.

To address my research problem I use the AAER database as evidence of misstating firms. I also calculate the F-score models proposed by Dechow et al. (2011) to predict misstating firms and I use the Fog index as proxy for readability. As mentioned by Dechow et al. (2011) the use of AAER database have advantage and disadvantage. The advantage is associated with the high level of confidence that the SEC has identified manipulating firms (low rate of the Type I error), and the disadvantage is that many manipulating firms are likely to go unidentified, because the SEC has a limited budget and consequently does not investigate a large number of firms. The Fog index is calculated based on MD&A section and not on other parts of annual financial statement as the notes or the report as whole, because the MD&A is more subject to managers' discretion. Basically, I add a readability variable on Model I and Model II developed by Dechow et al (2011) and analyze whether the readability is associated with the likelihood to detect a misstating firm and whether the model with readability variable improves the predictability of Dechow et al (2011) models.

Overall, my results suggest that readability level can be used to identify accounting misstatements. The readability has a direct and positive effect on the likelihood of detecting an AAER firm, improving the predictability of detecting AAER firms compared to Dechow et al (2011) models. The results are also confirmed in the robustness tests which use the length of MD&A section as the proxy for readability instead of Fog index.

My analysis, jointly with Larcker and Zarolyukina's (2012) analysis who use the linguistic feature of conference calls, can be viewed as an initial evidence about

the capacity to measure the quality of financial statements through readability proxies and consequently to help in predicting the likelihood of firm has accounting errors. Additionally, my results may help regulators such as SEC to reduce the cost of identifying suspicious firm of manipulating accounting numbers.

The remainder of the paper is organized in four sections. Section 2 provides a background about accounting misstatements literature and hypotheses development. The research design is presented in Section 3, where I describe the sample composition and the main tests. Next, Section 4 provides results and analyses. Finally, conclusions, limitations and suggestions for future research are presented in Section 5.

2.2 BACKGROUND AND HYPOTHESES DEVELOPMENT

Accounting misstatements and textual analyses have been the focus of several studies in accounting and finance literature (e.g. BENEISH, 1999, DECHOW et al., 2011; LI 2008; LEHAVY, LI and MERKLEY, 2011). The first issue is related to the effect of accounting errors in the efficient function of capital markets, influencing decisions of investors, auditors and regulators. The second topic is not an accounting issue, but it has been used in accounting and finance literatures as a method to analyze the communication process between firms and users of accounting information. For example Li (2008) uses textual analysis to measure the readability level of financial statements to analyze the relation of readability and firm performance. On the other hand, Li, Lundholm and Minnis (2013) use the textual analysis to construct a competition metric based on the number of times that specific words are cited in the annual financial statements. In this paper, I use the textual

analysis to verify whether readability can be view as a determinant of accounting misstatements.

Textual analysis has been used in accounting and finance literature in different ways. It is not the proposal of this paper to discuss about all different applications of textual analysis or make an extensive review, once Li (2011) already provides a comprehensive review of this literature[3]. I briefly discuss some papers which use the Fog index as the proxy for readability. Li (2008) uses the textual analysis to examine whether annual report readability has relation to firm performance. Li (2008) calculates the Fog index and the length of the document, and finds that annual financial statements of firms with lower earnings are harder to read. According to Li (2008) this evidence can be attributed to managers' discretion aiming to hide adverse information from investors. Lehavy et al. (2011) also use the Fog index and find evidence that the readability of 10-K fillings is related to the analyst following and the amount of effort incurred to generate reports. More specifically, they find that less readable reports are related with greater dispersion, lower accuracy, and greater overall uncertainty in analyst forecasts.

Dechow, Ge and Schrand (2010) provide an extensive review of external indicators of earnings misstatements. Therefore, I just highlight some papers in accounting misstatements literature which are more related with my research. Dechow et al. (2011) analyze the financial characteristics of misstating firm and develop a model to predict material accounting misstatements. The authors use the AAER database and identify the determinants of misstating firms, segregating the determinants in five groups: (i) accruals quality; (ii) financial performance; (iii) nonfinancial measures; (iv) off-balance-sheet activities; and (v) a market-based

[3] For more information see Li (2011).

measures. Dechow et al. (2011) develop three models combining the five groups of determinants. The output of their analysis is a scaled probability, namely *F-score*, which can be used as a signal of the likelihood of accounting misstatement. On average, their models classified correctly 68 percent of misstating firms.

The other related study is Larcker and Zarolyukina (2012). Using four different approaches, including one which using the AAER database, the authors estimate linguistic-based classification models of deceptive discussions during quarterly earnings conference calls. The authors develop the model selecting word categories that theoretically should be able to detect deceptive behavior by executives. Lacker et al. (2012)'s results suggest that the linguistic features of CEOs speech and CFOs speech in conference call narratives can be used to identify accounting misstatements.

My research builds on and is complementary to Dechow et al. (2011) and Larcker and Zarolyukina (2012). I take a different approach from Dechow et al. (2011), including another dimension of determinants, related to readability, on models which predicting accounting misstatements. It is important to highlight that my approach is not a critique or a substitution of Dechow et al.'s (2011) approach. On the contrary, my approach should be view as a complementary study or a next step of their works. In term of Larcker and Zarolyukina's (2012) study my research differs on the source of accounting information and the type of methodology used to analyze linguistic features. I use the accounting information provided on 10-K report (mandatory disclosure) instead of a conference call. The other difference is that my paper use textual analysis to measure the readability of the MD&A section, whereas Larcker and Zarolyukina's (2012) approach is related on the identification of specific words used by CEOs and CFOs in conference calls.

My hypotheses are based on the fact that managers have incentives to obfuscate adverse information related to accounting problems or discretion decision as managing earnings. An evidence of this managers' behavior is the result presented in the study developed in chapter 1. Assuming that managers have more discretion on the text of MD&A than others part of 10-K report, I hypothesize that:

H1: The readability of MD&A section is a determinant of misstating firms.

H2: The readability of MD&A section improves the predictability of accounting misstating models.

2.3 RESEARCH DESIGN

2.3.1 Data and sample description

The initial point to compose the final sample is the AAER issued by SEC[4]. Since May 17th, 1982, when the first AAER was issued, more than 3,000 investigations were concluded by SEC until September 2010. The Figure 2 shows the evolution year by year of the volume AAERs issued. After 1994, the number of investigations which were concluded increases considerably and the year 2003 has the highest number of AAER, totally 237 enforcement actions by SEC.

Each AAER refers to one or more involving parties as firm, managers, auditors etc. and can be related to one or more period: years or quarters. Therefore the relation between AAER and misstating firm-year is not direct. Specifically for this paper, the focus is not the AAER date, but the year which SEC investigation point as misstating firm-year. In other word, the base is the year which firms manipulated its accounting number.

[4] I am grateful to Patricia Dechow, for providing the AAER database on her personal website.

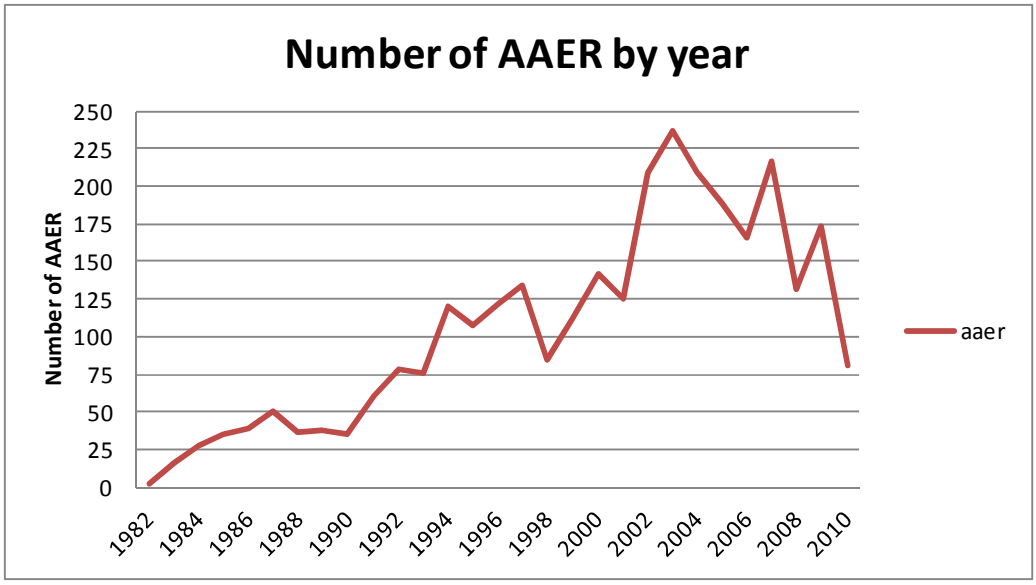

Figure 2. Empirical distribution of AAER between years 1982 to 2010.

The 3,052 AAERs generate 1,540 firm-year observations and 508 unique firms. The 1996 cutoff and the requirement to have *cik* are necessary to obtain financial statement from the Edgar database and to get accounting variables from the COMPUSTAT database. After this cutoff, the sample composition is 588 firm-year observations as demonstrated in Panel A of Table 9. Additionally, I excluded firms from financial service industry (SIC 6000-6999) and utility service industry (SIC 4400-5000) because disclosure requirements and accounting rules are significantly different for these industries. Finally, I excluded all firm-year which are not possible to obtain the MD&A section. After all exclusions my sample comprises 216 firm-year and 110 unique firms. Table 9, panel B provides the sample distribution by year. The year with more observation is 1999 with 39 cases and the year with less observation is 2005 with just 5 cases.

TABLE 9: SAMPLE SELECTION

Panel A: Sample Description - 1996 to 2005

	N
AAER Firm-year with gvkey	588
Less financial service industry and utility service	(193)
Less unable to obtain MD&A section on Edgar	(179)
Firm-year observations	216
Unique firms	110

Panel B: Distribution of Misstated firm-year

Year	Firm-years	Percentage
1996	24	11.11%
1997	33	15.28%
1998	31	14.35%
1999	39	18.06%
2000	17	7.87%
2001	22	10.19%
2002	17	7.87%
2003	19	8.80%
2004	9	4.17%
2005	5	2.31%
Total	216	100.00%

2.3.2 Proxy for Readability

The readability proxy used in this study is the Fog index. The proxy is already presented previously in section 1.3.2.

As a robustness test, I use another proxy of readability, which is the length of MD&A section. The length is calculated as the natural logarithm of the number of words. The interpretation is trivial and following the Fog index interpretation where the higher it is more difficult to understand the text or less readable it is.

$$LENGTH = \log(number\_of\_words) \quad (2.1)$$

2.3.3 Main Tests and Variables Definitions

The starting point to develop my main test is the logistic models: Model I (equation 2.2) and Model II (equation 2.3) proposed by Dechow et al. (2011) to identify misstating firm.

$$AAER_{it} = \gamma_1 + \gamma_2 rsst\_acc_{it} + \gamma_3 ch\_rec_{it} + \gamma_4 ch\_inv_{it} + \gamma_5 soft\_assets_{it} + \gamma_6 ch\_cs_{it} + \gamma_7 ch\_roa_{it} + \gamma_8 issue_{it} + \varepsilon_{it} \quad (2.2)$$

$$AAER_{it} = \gamma_1 + \gamma_2 rsst\_acc_{it} + \gamma_3 ch\_rec_{it} + \gamma_4 ch\_inv_{it} + \gamma_5 soft\_assets_{it} + \gamma_6 ch\_cs_{it} + \gamma_7 ch\_roa_{it} + \gamma_8 issue_{it} + \gamma_9 ch\_emp_{it} + \gamma_{10} leasedum_{it} + \varepsilon_{it} \quad (2.3)$$

where the dependent variable is equal to one for firm-years involving a misstatement, and zero otherwise. All independent variables are defined in Table 10 and the motivation to each misstatement determinants is presented in Dechow et al. (2011)[5].

Basically, the inclusion of accrual quality variables are justified because earnings are primarily misstated via the accrual component of earnings according to a large body of literature (e.g. Healy, 1985; Jones, 1991; Dechow et al., 1995). *RSST accruals* is equal to change in noncash net operating assets and follow the model proposed by Richardson, Sloan, Soliman and Tuna (2005). Additionally, it also includes *change in receivables* and *change in inventory*, both directly related with metrics followed by investors as sales growth and gross margin, respectively. I also add *% soft assets*, which represents the percentage of assets that are neither cash nor PP&E. According to Barton and Simko (2002) firms with greater net operating assets having more accounting flexibility to report positive earnings surprise.

[5] For more information see Dechow et al 2011.

TABLE 10: VARIABLES DEFINITIONS

Variable	Abbrev.	Pred sign	Calculation
Accrual quality variables			
RSST accruals	*rsst_acc*	+	(ΔWC + ΔNCO + ΔFIN) / Average total assets, where WC = [Current Assets (DATA 4) - Cash and Short-term Investments (DATA 1)] - [Current Liabilities (DATA 5) - Debt in Current Liabilities (DATA 34)]; NCO = [Total Assets (DATA 6) - Current Assets (DATA 4) - Investments and Advances (DATA 32)] - [Total Liabilities (DATA 181) - Current Liabilities (DATA 5) - Long-term Debt (DATA 9)]; FIN = [Short-term Investments (DATA 193) + Long-term Investments (DATA 32)]-[Long-term Debt (DATA 9) + Debt in Current Liabilities (DATA 34) + Preferred Stock (DATA 130)]; following Richardson et al. 2005.
Change in receivables	*ch_rec*	+	ΔAccounts Receivable (DATA 2)/ Average total assets
Change in inventory	*ch_inv*	+	ΔInventory (DATA 3)/ Average total assets
%Soft assets	*soft_assets*	-	(Total Assets (DATA 6) - PP&E (DATA 8) - Cash Equivalent (DATA 1)) / Total Assets (DATA 6)
Performance variables			
Change in cash sales	*ch_cs*	-	Percentage change in cash sales [Sales (DATA 12) - Δaccounts Receivable (DATA 2)]
Change in return on assets	*ch_roa*	+	[Earnings$_t$ (DATA 18) / Average total Assets$_t$] - [Earnings$_{t-1}$ (DATA 18) / Average total Assets$_{t-1}$]
Nonfinancial variables			
Abnormal change in employees	*ch_emp*	-	Percentage change in the number of employees (DATA 29) - Percentagechange in Assets (DATA 6)
Off-balance-sheet variables			
Existence of operating leases	*leasedum*	+	An indicator variable coded 1 if future operating lease obliagtions are greater than zero
Market-related incentives			
Actual issuance	*issue*	+	An indicator variable coded 1 if firm issued securities during year *t* (i.e., an indicator variable coded 1 if DATA 108 > 0 or DATA 111 > 0)
Readability Variables			
FOG Index	*fog*	+	(word per sentence + percent of complex words)*0.4 based on MD&A section from 10-K report
Length	*length*	+	Logarithm of number the words of MD&A section from 10-K report

Assuming that managers can mask deteriorating performance, *change in cash sales* and *change in return on assets* are the two variables related to firm performance included in the model. The intuition is that managers can encourage credit sales which are subject to accruals management and consequently reduce cash sales volume which are not subject to accruals management. According to Graham et al. (2005) managers prefer to show positive growth in earnings, therefore the need to analyze *change in return on assets*.

The *abnormal change in employees* is the nonfinancial measures included in the model. To boost the earnings managers can reduce expense related to employee headcount. I add the *existence of operating leases*, because they are a source of off-balance-sheet financing and enable manager to record lower expenses early on in the life of the lease. Finally, it is also add a variable related to market incentive which is computed from variables in the financial statement, the *actual issuance*. The intuition is detect a firm's need to raise additional capital, thus *actual issuance* identify whether firm has issued new debt or equity during misstatement year.

Dechow et al. (2011) also proposed a third model which is similar the Model II, but include market-adjusted stock return and lagged market-adjusted stock return. I decided to not include Dechow et al. (2011)'s third model on my analyses, because it does not add significant contributions and it also add more restriction on the final sample.

To examine whether the readability level of MD&A section helps to predict whether firm is a misstating firm I use modified versions of logistic models proposed by Dechow et al. (2011).

$$AAER_{it} = \beta_1 + \beta_2\, fog_{it} + \sum_{k=3}^{9} \gamma_k\, controls\_version1_{it} + \varepsilon_{it} \qquad (2.4)$$

$$AAER_{it} = \beta_1 + \beta_2\, fog_{it} + \sum_{k=3}^{9} \gamma_k controls\_version2_{it} + \varepsilon_{it} \quad (2.5)$$

As mentioned early, I add the Fog index (proxy for readability) in the models and control for all others determinants of accounting misstatement evidenced by Dechow et al. (2011). The inclusion of readability variable is based on assumption that managers have an incentive to obfuscate information relate to accounting problems or discretion decision as managing earnings. Evidence of this behavior is showed in chapter 1 of this study. The *controls_version1* is equal to all variables presented in equation 2.2, and the *controls_version2* is equal to all variables presented in equation 2.3.

Following Dechow et al.'s (2011) approach to examine the quality of the models, I analyze the predicted probabilities that the model assigns to each observation. It is important to highlight that the models analysis is limited to the joint fact that a firm is misstated and received an AAER from the SEC. For the situation where a firm is a misstated firm but it is not caught by the SEC is not possible to test the performance of models. To obtain the predicted values for each firm-year, I use the estimated coefficients and plug each firm's characteristics into the model. The predicted probability is obtained by:

$$\Pr obability = \frac{e^{(\Pr edictedValue)}}{(1+e^{(\Pr edictedValue)})} \quad (2.6)$$

Next, in order to calculate the *F-score*, I divide the probability (equation 2.6) by the unconditional expectation of misstatement (equal to the number of misstatement observations divided by the total number of observations). The *F-score* is equal to:

$$F\_score = \frac{\text{Probability}}{Unconditional\ \text{Probability}} \quad (2.7)$$

If *F-score* is equal to 1.00, then the firm's probability of misstatement is equal to the unconditional expectation. Therefore, *F-score* less than 1.00 it indicates lower probability of misstatement than the unconditional expectation and *F-score* greater than 1.00 indicates higher probability of misstatement compare to unconditional expectation. Following Dechow et al. (2011), I define the *F-score* cutoff of 1.00 to analyze the power of the models.

2.4 RESULTS

2.4.1 Descriptive Statistics and Misstating firm-year analysis

Table 11 presents descriptive statistics of two groups: (i) misstatements firm-year and (ii) all firms listed on the COMPUSTAT Annual File between 1996 and 2005, which are possible to calculate the Fog index. I limit the sample to 1996, because before that year there is no 10-K report available to download form EDGAR database. Additionally, Table 11 also presents the test of difference in means between the two groups.

Although the composition of my sample and time-series period differs from that used in Dechow et al. (2011) the descriptive statistics and the results of difference in mean test are similar. All the accruals quality variables related to misstating firm present an unusual behavior compare to non-misstating firm. For misstating firms the change in noncash net operating assets (*RSST_accruals*) is 9.1 percent of assets, whereas for non-misstating firm this measure is 3.8 percent of assets. *Change in receivables* and *change in inventory* for misstating firm are 4.9

percent of assets and 2.2 percent of assets, respectively, which are higher than 2.0 percent of assets in *change receivables* and 0.8 percent of assets in *change in inventory* for non-misstating firm. Additionally, misstating firms present on average higher net operating assets (*%Soft_assets*) than non-misstating firms in approximately 11%.

Regarding performance variables, *change in cash sales* for misstating firms is about twice as large as for non-misstating firms. Although, the difference in cash sales is statistically significant it is not in predicted direction, similar to Dechow et al.'s (2011) results. There is no difference on *change in return on assets* between the two groups. The results for nonfinancial variables, off-balance-sheet variables and market-related variables are statistically different, at least in 5%, and all in the predicted directions.

Although the difference in readability, measured by Fog index, is in predicted direction it is not statistically different. One possible reason for this result is the fact that some manipulating firms are not investigated and consequently they are not identified by SEC as a misstating firm. Therefore, these unidentified firms can be influencing the level of readability presented by non-misstating firms. However, for the alternative proxy (length), used in robustness test, there is difference between misstating firms and non-misstating firms. For misstating firms the *length* of MD&A section is higher than non-misstating firms. The result is statistically different and in the predicted direction.

TABLE 11: DESCRIPTIVE STATISTICS ON MISSTATEMENT FIRM-YEAR VERSUS COMPUSTAT FIRM-YEAR

	Misstatement years			Compustat firm-years				Misstate - Compustat		
Variable	N	Mean	Median	N	Mean	Median	Pred Sign	Diff. in Mean	Two-tailed p-value	t-statistics
Accruals quality variables										
RSST accruals	211	0.091	0.051	26545	0.038	0.028	+	0.053	0.005	2.84
Change in receivables	214	0.049	0.028	28629	0.020	0.011	+	0.030	0.000	5.36
Change in inventory	213	0.025	0.000	28498	0.008	0.000	+	0.017	0.000	4.51
% Soft assets	215	0.670	0.690	28861	0.557	0.588	+	0.113	0.000	6.34
Perfromance variables										
Change in cash sales	211	0.348	0.200	27941	0.187	0.084	-	0.161	0.015	2.44
Change in return on assets	211	-0.010	-0.005	28304	-0.005	0.000	+	-0.005	0.694	-0.39
Nonfinancial variables										
Abnormal change in employees	199	-0.155	-0.077	26271	-0.083	-0.033	-	-0.073	0.038	-2.08
Off-balance-sheet variables										
Existence of operating leases	216	0.894	1.000	29032	0.811	1.000	+	0.083	0.002	3.09
Market-related variables										
Acutal issuance	216	0.972	1.000	29032	0.868	1.000	+	0.104	0.000	4.52
Readability proxies										
Fog	216	18.440	18.208	29032	18.278	18.022	+	0.161	0.421	0.80
Length	216	8.476	8.592	29032	8.357	8.418	+	0.118	0.051	1.95

The sample is composed by all firms which have CIK available between 1996 to 2005.

All variables are defined in Table 2. All the continuous control variables are winsorized at 1% and 99%.

2.4.2 Determinants of Misstatements

To analyze the effect of readability and others determinants in predicting accounting misstatements I run a logistic model, where the dependent variable is an indicator variable equal to one for misstating firm-year (AAER) and zero otherwise. Table 12 presents the results of logistic model of four different approaches. Model 1 and Model 2 are exactly the same models proposed by Dechow et al. (2011). Model 1 contemplates all finance statements variables as predictors, whereas Model 2 adds off-balance variables and nonfinancial variables. Model 3 and Model 4 are similar to Model 1 and Model 2, respectively, but they include the Fog index as the proxy for readability.

Based on Model 1 and Model 2 c*hange in receivables*, *% soft assets* and *actual issuance* are the determinants which have positive and significant effect in predicting misstatements. These three determinants are the same previously identified by Dechow et al. (2011) as those with the greatest impact in predicting misstatements. The coefficients of others determinants are not statistically significant.

According to Model 3 and Model 4, the Fog index presents positive and statistically significant coefficients at 10% and 5% levels, respectively. These results confirm the hypothesis that readability can be useful in predicting misstatement after controlling for all determinants previously identified by Dechow el al. (2011).

TABLE 12: DETERMINANTS OF MISSTATEMENTS AND DEVELOPMENT OF THE F-SCORE

	Model 1		Model 2		Model 3		Model 4	
	Financial statement variables		Add off-balance-sheet and nonfinancial variables		Financial statement variables add reliability variable		Add off-balance-sheet, nonfinancial variables and reliability variable	
Variable	Coeff.	Wald Chi-square	Coeff.	Wald Chi-square	Coeff.	Wald Chi-square	Coeff.	Wald Chi-square
Intercept	-7.397	217.503 ***	-7.696	174.707 ***	-7.856	191.060 ***	-8.203	158.240 ***
RSST accruals	0.360	1.388	0.333	0.962	0.363	1.424	0.337	0.991
Change in receivables	2.681	9.314 ***	2.594	8.021 ***	2.658	9.187 ***	2.573	7.926 ***
Change in inventory	1.597	1.827	1.697	1.923	1.647	1.942	1.750	2.046
% Soft assets	2.134	39.391 ***	2.071	34.592 ***	2.167	40.349 ***	2.103	35.475 ***
Change in cash sales	0.072	0.825	0.085	1.028	0.069	0.772	0.082	0.974
Change in return on assets	-0.378	0.908	-0.382	0.874	-0.374	0.897	-0.377	0.860
Actual issuance	1.193	6.890 ***	1.293	6.496 ***	1.199	6.952 ***	1.298	6.536 ***
Abnormal change in employees			-0.104	0.550			-0.103	0.537
Existence of operating leases			0.228	0.832			0.248	0.971
Fog					0.024	3.326 *	0.025	3.689 **
Misstating firm-years	207		195		207		195	
Nonmisstating firm-years	25572		24712		25572		24712	

Dependent variable is equal to one if misstating firm-year, zero otherwise.

All variables are defined in Table 10. All control variables are winsorized at 1% and 99%.

2.4.3 F-score and Sensitivity Analysis of Models

To examine the quality of models I perform my analysis based on the F-score (DECHOW et al., 2011). Table 13, panel A presents the frequency of misstating firm and non-misstating firm into five portfolios. To determinate each portfolio I rank firm-years in quintiles based on the magnitude of their *F-scores*. The expected level of each group in each portfolio is 20 percent. As noted in all models the non-misstating firms present around 20 percent in each portfolio as expected. However, misstating firms presents abnormal distribution concentrate in the portfolio 5. Model 1 and Model 2, which do not consider the readability as a determinant, indicates that 65.70% and 67.18% of misstatement firms, respectively, are in quintile 4 and 5.

The models that include the readability variable as a determinant of misstating firm present an abnormal distribution more concentrated in portfolio 4 and 5 than models that do not include readability. Model 4 presents 67.63% of misstating firm distributed in quintiles 4 and 5, which is higher in approximately 2% than Model 1. On the other hand, model 5 presents 68.72% of misstating firm distributed in quintiles 4 and 5, which is higher in about 1.5% than Model 2.

In Panel B of Table 13, I analyze the sensitivity of each model and determine Type I and Type II errors rates for an *F-score* cutoff of 1.00. Model 3, which includes financial statements variables and readability variable, classifies correctly 60.81% of all cases. With respect to the classification of misstating firm, Model 3 correctly identify 138 of the 207 misstate cases (sensitivity equal to 66.67%).

TABLE 13: *F-SCORE* AND SENSITIVITY OF MODELS

Panel A: Rates of misstating and no-misstating firms for each model

	Model 1			Model 2			Model 3			Model 4		
	N	Min. F-score	% of total	N	Min. F-score	% of total	N	Min. F-score	% of total	N	Min. F-score	% of total
Quintile 1												
Misstate	7	0.183	3.38%	6	0.167	3.08%	7	0.172	3.38%	6	0.158	3.08%
No-misstate	5,148	0.037	20.13%	4,975	0.031	20.13%	5,148	0.034	20.13%	4,975	0.027	20.13%
Quintile 2												
Misstate f	26	0.422	12.56%	26	0.423	13.33%	25	0.410	12.08%	28	0.414	14.36%
No-misstate	5,130	0.412	20.06%	4,956	0.416	20.06%	5,131	0.409	20.06%	4,954	0.410	20.05%
Quintile 3												
Misstate	38	0.698	18.36%	32	0.691	16.41%	35	0.679	16.91%	27	0.682	13.85%
No-misstate	5,118	0.680	20.01%	4,949	0.684	20.03%	5,121	0.675	20.03%	4,954	0.678	20.05%
Quintile 4												
Misstate	**44**	**1.001**	**21.26%**	**45**	**0.993**	**23.08%**	**48**	**0.995**	**23.19%**	**47**	**0.986**	**24.10%**
No-misstate	5,112	0.999	19.99%	4,937	0.992	19.98%	5,108	0.992	19.97%	4,935	0.985	19.97%
Quintile 5												
Misstate	**92**	**1.444**	**44.44%**	**86**	**1.432**	**44.10%**	**92**	**1.443**	**44.44%**	**87**	**1.440**	**44.62%**
No-misstate	5,064	1.439	19.80%	4,895	1.430	19.81%	5,064	1.439	19.80%	4,894	1.428	19.80%

continue

Panel B: Sensitivity of model

	Model 1 predicted			Model 2 predicted			Model 3 predicted			Model 4 predicted		
Observed	Misstate	No-misstate		Misstate	No-misstate		Misstate	No-misstate		Misstate	No-misstate	
Misstate	**136**	71	207	**129**	66	195	**138**	69	207	**131**	64	195
No-misstate	10,164	**15,408**	25,572	9,718	**14,994**	24,712	10,034	**15,538**	25,572	9,621	**15,091**	24,712
	10,300	15,479	25,779	9,847	15,060	24,907	10,172	15,607	25,779	9,752	15,155	24,907
Misstate	**65.70%**	34.30%	0.80%	**66.15%**	33.85%	0.78%	**66.67%**	33.33%	0.80%	**67.18%**	32.82%	0.78%
No-misstate	39.75%	**60.25%**	99.20%	39.33%	**60.67%**	99.22%	39.24%	**60.76%**	99.20%	38.93%	**61.07%**	99.22%
Correct classification	(1)	60.30%			60.72%			60.81%			61.12%	
Sensitivity	(2)	65.70%			66.15%			66.67%			67.18%	
Type I errors	(3)	39.75%			39.33%			39.24%			38.93%	
Type II errors	(4)	34.30%			33.85%			33.33%			32.82%	

All observations are ranked based on their predicted probabilities (F-score) and sorted into quintiles. Minimum F-score is the minimum predicted probability based on estimate in

Table 12 to enter each quintile

(1) Correct classification is calculated as [(136 + 15,408) / 25,779].

(2) Sensitivity is calculated as (136 / 207).

(3) Type I errors are calculated as (10,164 / 25,572).

(4) Type II errors are calculated as (71 / 207).

The Type I error is observed when the model classifies a non-misstating firm as misstating firm incorrectly. Model 3 presents a Type I error rate equal to 39.24%. On the other hand, the Type II error is observed when the model classifies a misstating firm as non-misstating firm incorrectly. The Type II error rate of Model 3 is equal to 33.33%.

Model 4, which includes financial statements variables, performance variables off-balance-sheet variables and readability variables, classifies correctly 61.12% of all cases. With respect to the classification of misstating firm, Model 4 correctly identify 131 of the 195 misstate cases (sensitivity equal to 67.18%). Finally, model 4 presents a Type I error rate and a Type II error rate equal to 38.93% and 33.33%, respectively.

Taken together, the models which include the Fog index as proxy for readability, present a slightly better performance than the original models proposed by Dechow et al. (2011). The model 4 presents the best classification of misstating and non-misstating firms and consequently the lowest Type I and Type II errors rates. Therefore, this result is evidence that the readability level of MD&A section can be useful in order to indentify a misstating firm.

2.4.4 Robustness Tests

I run two robustness tests by changing the readability proxy. According to Li (2008) an alternative proxy for readability is the *length* of the document. Therefore I calculated the *length* of MD&A section for each firm-year. In the first robustness test I substitute the *Fog* by *length* and run the logistic regressions controlling for all others determinants of misstating firms proposed by Dechow et al. (2011). Next, I analyze the F-score and sensitivity of each model. The second robustness test I use both proxies of readability, *Fog* and *length*, in the model and proceed with all analyses.

Table 14 and Table 15 present results related to the alternative proxy for readability. Model 5 and Model 6 refers to the first robustness test, where *Fog* is substituted by *length*. The results evidence that *length* also helps to predict misstating firms. Additionally, the F-score and sensitivity analyses present results similar than those when *Fog* is used as proxy for readability.

Model 7 and Model 8 refers to the second robustness test, where *length* and *Fog* are jointly test. The results evidence that the *length* and *fog* still help to predict misstating firms and F-score and sensitivity analyses present results similar than those when *Fog* or *length* are used individually as proxy for readability.

Therefore, previous conclusions remain unchanged, with identical qualitative results. In other words, the readability can be useful to predict misstating firm even in the use of alternative proxy.

2.5 CONCLUSION

Cases of accounting manipulation or accounting fraud detected by SEC are rare events. However, the understanding of this event is fundamental to the efficient function of capital markets. For that reason accounting researchers have attempted to identify the determinants of misstating firms and consequently develop models that help to explain the event. Usually, prior studies rely only on financial statements variables as determinants of misstatements.

TABLE 14: DETERMINANTS OF MISSTATEMENTS AND DEVELOPMENT OF THE F-SCORE - ROBUSTNESS TESTS

Variable	Model 5 Financial statement variables Coeff.	Wald Chi-square		Model 6 Add off-balance-sheet and nonfinancial variables Coeff.	Wald Chi-square		Model 7 Financial statement variables add reliability variable Coeff.	Wald Chi-square		Model 8 Add off-balance-sheet, nonfinancial variables and reliability variable Coeff.	Wald Chi-square	
Intercept	-9.203	99.539	***	-9.290	91.098	***	-9.883	102.290	***	-10.019	94.077	***
RSST accruals	0.373	1.504		0.353	1.083		0.377	1.555		0.359	1.130	
Change in receivables	2.790	9.942	***	2.695	8.555	***	2.766	9.817	***	2.675	8.477	***
Change in inventory	1.752	2.155		1.837	2.213		1.821	2.328		1.908	2.387	
% Soft assets	2.161	40.055	***	2.099	35.270	***	2.204	41.350	***	2.142	36.450	***
Change in cash sales	0.068	0.738		0.082	0.949		0.064	0.657		0.078	0.867	
Change in return on assets	-0.391	0.987		-0.392	0.929		-0.386	0.974		-0.386	0.912	
Actual issuance	1.111	5.937	**	1.227	5.820	**	1.115	5.987	**	1.230	5.846	**
Abnormal change in employees				-0.095	0.458					-0.092	0.437	
Existence of operating leases				0.183	0.535					0.203	0.647	
Length	0.221	5.543	**	0.199	4.254	**	0.232	6.421	***	0.212	5.068	**
Fog							0.030	5.689	**	0.031	5.915	**
Misstating firm-years	207			195			207			195		
Non-misstating firm-years	25572			24712			25572			24712		

Dependent variable is equal to one if misstating firm-year, zero otherwise.

All variables are defined in Table 2. All control variables is winsorized at 1% and 99%.

TABLE 15: *F-SCORE* AND SENSITIVITY OF MODELS - ROBUSTNESS TESTS

Panel A: Rates of misstating and non-misstating firms for each model

	Model 5			Model 6			Model 7			Model 8		
	N	Min. F-score	% of total	N	Min. F-score	% of total	N	Min. F-score	% of total	N	Min. F-score	% of total
Quintile 1												
Misstate	10	0.192	4.83%	11	0.173	5.64%	11	0.178	5.31%	9	0.161	4.62%
No-misstate	5,145	0.026	20.12%	4,970	0.023	20.11%	5,144	0.023	20.12%	4,972	0.020	20.12%
Quintile 2												
Misstate	18	0.402	8.70%	16	0.426	8.21%	20	0.404	9.66%	18	0.406	9.23%
No-misstate	5,138	0.401	20.09%	4,966	0.406	20.10%	5,136	0.397	20.08%	4,964	0.401	20.09%
Quintile 3												
Misstate	40	0.669	19.32%	36	0.675	18.46%	35	0.658	16.91%	34	0.668	17.44%
No-misstate	5,116	0.662	20.01%	4,945	0.670	20.01%	5,121	0.658	20.03%	4,947	0.664	20.02%
Quintile 4												
Misstate	**48**	**1.010**	**23.19%**	**48**	**0.985**	**24.62%**	**52**	**0.979**	**25.12%**	**51**	**0.981**	**26.15%**
No-misstate	5,108	0.985	19.97%	4,934	0.981	19.97%	5,104	0.975	19.96%	4,931	0.971	19.95%
Quintile 5												
Misstate	**91**	**1.463**	**43.96%**	**84**	**1.480**	**43.08%**	**89**	**1.458**	**43.00%**	**83**	**1.451**	**42.56%**
No-misstate	5,065	1.454	19.81%	4,897	1.443	19.82%	5,067	1.457	19.81%	4,898	1.447	19.82%

Panel B: Sensitivity of model

		Model 5 predicted			Model 6 predicted			Model 7 predicted			Model 8predicted		
Observed		Misstate	No-misstate		Misstate	No-misstate		Misstate	No-misstate		Misstate	No-misstate	
Misstate		**139**	68	207	**131**	64	195	**137**	70	207	**130**	65	195
No-misstate		9,951	**15,621**	25,572	9,565	**15,147**	24,712	9,807	**15,765**	25,572	9,475	**15,237**	24,712
		10,090	15,689	25,779	9,696	15,211	24,907	9,944	15,835	25,779	9,605	15,302	24,907
Misstate		**67.15%**	32.85%	0.80%	**67.18%**	32.82%	0.78%	**66.18%**	33.82%	0.80%	**66.67%**	33.33%	0.78%
No-misstate		38.91%	**61.09%**	99.20%	38.71%	**61.29%**	99.22%	38.35%	**61.65%**	99.20%	38.34%	**61.66%**	99.22%
Correct classification	(1)		61.14%			61.34%			61.69%			61.70%	
Sensitivity	(2)		67.15%			67.18%			66.18%			66.67%	
Type I errors	(3)		38.91%			38.71%			38.35%			38.34%	
Type II errors	(4)		32.85%			32.82%			33.82%			33.33%	

All observations are ranked based on their predicted probabilities (F-score) and sorted into quintiles. Minimum F-score is the minimum predicted probability based on estimate in Table 6 to enter each quintile.

(1) Correct classification is calculated as [(139 + 15,621) / 25,779].

(2) Sensitivity is calculated as (139 / 207).

(3) Type I errors are calculated as (10,090 / 25,572).

(4) Type II errors are calculated as (68 / 207).

In this paper I take a different approach and use a different source of accounting information. Instead of using financial variables, I take into consideration textual analysis to calculate the level of readability of MD&A section, once managers have incentive to lower the readability of MD&A to obfuscate information relate to accounting problems or discretion decision as managing earnings. Therefore, this paper is an exploratory study which search for evidence that the readability, measured by Fog index, can be useful in predicting accounting misstatements.

Results suggest that after controlling for other misstatements determinants as financial statements variables, off-balance-sheet variables and market-related variables, the readability increase the probability to detect a misstatement event. Based on F-score and sensitivity analysis proposed by Dechow et al. (2011), I find evidence that models which include the Fog index as a proxy for readability present a slight better performance than models without readability. Results are robust even using an alternative proxy for readability as length of the document. As all exploratory study, my findings are subject to limitations. The main limitation is that results are restricted to firms which are investigate and caught by SEC. Therefore, results are not extended to firms which manipulating or fraud their accounting numbers, but are not identified by SEC as misstating firms.

Finally, my analysis provides insights to financial statement users, especially to investors, auditors and regulators, about a new characteristic of misstating firm. In terms of future research, it would be useful to extend the use of studies involving alternatives approaches and accounting sources aiming to improve the misstatement models. One possibility would be investigate in more refined way whether the reason indicated by SEC can be related with a specific managers' behavior when they are writing the MD&A section. For example, whether SEC indicates that the misstatement

is related with credit sales, then researchers can be analyze whether managers use less words related to receivables or credit.

Chapter 3

3 THE READABILITY EFFECT ON THE MARKET'S MISPRICING OF EARNINGS

3.1 INTRODUCTION

The main objective of this paper is to investigate whether the level of readability influences earnings mispricing by investors. Specifically, I test whether investors are able to understand the earnings persistence for loss and profit firms with different levels of financial statements' readability. Given that managers may be opportunistically structuring the annual reports to hide adverse information from investors and investors' limited attention, I expected that for firms with annual report easier to read the market correctly price earnings persistence as long as less readable annual reports would lead to mispricing.

Although there is a wide documented literature about the earnings mispricing, accruals anomaly and their extensions (e.g. SLOAN, 1996, RICHARDSON et al., 2005, DECHOW et al, 2008), most of academic and practitioner communities still demand for empirical discovery and investigation of new anomalies or signal and implementation of trading strategies (RICHARDSON et al., 2010). In addition of this argument, the motivation of this paper is conducted by the need to better understand the effects and consequences of the financial report readability on the prediction of earnings and returns.

Prior literature, following Sloan's (1996) hypothesis that naive investor fixation on bottom line earnings or investors' limited attention, show that investors do not understand completely the persistence of earnings and their components (e.g. THOMAS, 2000; XIE, 2001; COLLINS ET AL., 2003). Based on the argument that in

different environments the market does not fully understand the persistence of current earnings for future earnings, Thomas (2000) finds that foreign earnings tend to be more persistent than domestic earnings, and investors do not recognize this behavior, underestimating this type of earnings. By decomposing accruals in two components Xie (2001) shows that both normal and abnormal accruals are overestimated by investors, and this evidence is more pronounced on the component that managers have more discretionary power and he attributes this result with earnings management practices.

Some papers analyze the contribution of accounting intermediaries, such as sophisticated investors, analyst and auditors to alert or to identify problems related to future persistence of earnings and their components (e.g. BARTOV et al., 2000, COLLINS et al., 2003; BRADSHAW et al., 2001). However, the evidence in this literature is mixed. Collins et al. (2003) find that firms with sophisticated investors assign right values to accruals persistence, but firms with unsophisticated investors have their accruals mispriced. On the other hand, Bradshaw et al. (2001) show that two important types of professional investor intermediaries, analysts and auditors, who supposedly have more knowledge about market and could help investors to better understand the information, do not alert investors to the future earnings problems related with high accruals. To my knowledge, the investor sophistication literature does not consider, except by Lee (2012), the information which investors are faced can have different levels of difficulty, and then it does not control or conditions the effect of investor sophistication by the level of complexity to understand the information. Therefore, my paper fills this gap in the literature by analyzing the effect of readability on the pricing of earnings persistence.

Following Lee (2008), in order to address my research problem I define the level of readability based on the Fog index from the computational linguistics literature. The Fog index indicates the number of years of formal education a reader of average intelligence would need to read and understand the text. The readability is calculated based on Management Discussion and Analysis (MD&A) section, because its represents the section which managers have more flexibility to analyze the firms' result. Following Sloan (1996), I proceed with non-linear regression-based tests (MISHIKIN, 1983) to identify whether the market correctly incorporate in price the persistence of current earnings.

First, I analyze the persistence of current earnings for the full sample. After, I segregate the sample in loss and profit firms, because as showed by Li (2008) the persistence of earnings for loss and profit firms is differently related with the level of annual reports' readability. Finally, I test in each situation how the market pricing earnings conditioned on type of earnings and conditioned on the level of readability.

The results indicate that for loss firms the readability affects the earnings mispricing. Specifically, for loss firms with annual report harder to read the market understates earnings' persistence. On the other hand, for loss firms with annual report easier to read the market correctly price earnings persistence. However, for profits firms the results are not confirmed. Therefore, this paper provides insight on one factor (the readability level) which may contribute to earnings mispricing, but just for loss firms.

This paper contributes to the literature at least in two ways. First, I add to the earnings quality and disclosure quality literature by demonstrating that managers strategically use corporate disclosure in order to mislead or to influence the investors' understanding about firms' performance. Second, I add to earnings and their

component pricing literature by showing that investors do not recognize the real persistence of earnings when they are faced on annual reports which are harder to read, at least for loss firms.

The remainder of the paper is organized in four sections. Section 3.2 provides a background about earnings pricing literature and hypotheses development. The research design is presented in Section 3.3, where I describe the sample composition and the main tests. Next, Section 3.4 provides results and analyses. Finally, conclusions, limitations and suggestions for future research are presented in Section 3.5.

3.2 BACKGROUND AND HYPOTHESES DEVELOPMENT

Sloan (1996) is the seminal paper which analyzes whether investor correctly price earnings and their components (cash flow and accruals) persistence. Sloan (1996) finds evidence that investors “fixate” on earnings, falling to distinguish between the different properties of cash flow and accruals components. After Sloan (1996) researchers have been working on extensions and complementary analysis of initial evidence of market mispricing (e.g. XIE, 2001, COLLINS et al., 2003, THOMAS, 2000).

Collins et al. (2003) analyze the accruals mispricing phenomena by examining the role of investor sophistication in evaluating the valuation implications of accruals. The authors find evidence that investor sophistication reduce the mispricing of accruals components, whereas unsophisticated investors remain overstates the accruals persistence. Although Collins et al. (2003) find that investor sophistication reduces the accruals mispricing, they also find that abnormal return can be earned with a trading strategic for stocks primarily held by sophisticated investors. Therefore,

even sophisticated invertors seems do not comprehend completely the information contained in earnings and their components. One possible reason, but not highlighted and analyzed by the authors is that even sophisticated investors are subject to the complexity to read different annual reports.

In terms of readability, Li (2008) hypothesizes and finds evidence that profit firms with more persistent earnings have annual report easier to read, whereas profit firms with more transitory earnings have annual report harder to read. Additionally, Li (2008) hypothesizes that for loss firms with transitory losses the annual report would be more readable than for loss firms with permanent losses. However, for loss firm Li (2008) do not find evidence statistically significant. These hypotheses are based on that permanent profits are better than transitory earnings and that transitory losses are better than permanent losses. Therefore, managers have incentives to write annual reports easier to read when they are faced on permanent profits or transitory losses. On the other hand, managers also may have incentives to obfuscate information writing annual reports more difficult to read when firms have transitory earnings or permanent losses.

One recent and competitive study (LEE, 2012) shows that the difficulty to process information is one of the reasons which contribute to the delayed price reaction to earnings news. Lee (2012) uses the readability proxies developed by Li (2008), length of reports and Fog index and finds evidence that more difficult-to-read disclosures prolong the price discovery process and lengthen the price drift after earnings announcement. My paper distinguishes from Lee (2012) in two aspects. First, I focus on an anomaly associated to year event, as accrual anomaly, whereas Lee (2012) focuses on post earnings announcement drift which is an anomaly associated to quarter event. Collins and Hribar (2000) provide evidence that those

two types of anomaly are different and one effect does not eliminate another. Additionally, I analyze the sample in a segregated way, by loss and profit firms, once they present different behavior related to their earnings persistence (LI, 2008).

Assuming that managers have incentives to strategically use corporate disclosure activity in order to mislead or to influence the investors' understanding about firms' earnings persistence and that firms with less readable information require additional level of investors' market knowledge to understand the properties of earnings, I hypothesize that:

H1(a): Firms with more permanent losses have MD&A section less readable than firms with more transitory loss.

H1(b): Firms with more transitory profits have MD&A section less readable than firms with more permanent profit.

H2: Earnings expectations embedded in share prices more accurately reflect the differential persistence of earnings with MD&A section more readable relative to firms with MD&A section less readable.

3.3 RESEARCH DESIGN

3.3.1 Data and Sample description

The sample is composed by all firms with available data necessary to estimate the earnings persistence and to calculate the one year ahead abnormal return. Finance statements data are collected from the Compustat Annual Industrial and Research files, and returns data are collected from CRSP files for NYSE, AMEX, and NASDAQ firms. Additionally, firms must have the 10-K report available to download on Edgar database. Using the Perl programming language, I download all available

10-k filings from Edgar and calculate the Fog index for MD&A section. The final sample for composed by 32,338 firm-years.

3.3.2 Proxy for Readability

The readability proxy used in this study is the Fog index. The proxy is already presented previously on section 1.3.2.

To define firms which have low level of FOG (more readable) and firms which have high level of FOG (less readable) I use the median of FOG for full sample. Therefore, firms which have FOG below the median are classified as low FOG, whereas firms which have FOG above the median are classified as high FOG.

3.3.3 Persistence of Earnings

First, I analyze the persistence of current earnings on one year ahead earnings for the full sample and then for segregates samples of loss and profit firm. I estimate the earnings persistence in the following regression:

$$Earn_{t+1} = \beta_0 + \beta_1 Earn_t + \upsilon_{t+1} \quad (3.1)$$

where *Earn* is equal to net income before extraordinary items scaled by average total asset. The β_1 coefficient represents the persistence of current earnings. After that, I estimate earnings persistence conditioned on the level of readability, following the regression:

$$Earn_{t+1} = \alpha_0 + \alpha_{0H} H_t + \alpha_1 Earn_t + \alpha_{1H} H\_Earn_t + \upsilon_{t+1} \quad (3.2)$$

where *H* represent an indicator variable equals one for firms with high Fog and zero for firms with low Fog. The *H_Earn* represents the interaction term between *H* and *Earn* variables. Therefore, the α_1 coefficient measures the earnings persistence for

firm with low level of FOG. The α_{1H} coefficient measures the incremental effect of earnings persistence related to firms with high level of FOG. Based on Li's (2008) result I expect that for profit firms the α_{1H} coefficient is negative. In other words, I expect that profit firms with MD&A section less readable present earnings less persistent. On the other hand, although Li's (2008) result is in correct direction, but it is not statistically significant, I expect that for loss firm the α_{1H} coefficient is positive. In other words, I expect that loss firms with MD&A section less readable present earnings more persistent.

3.3.4 Market Pricing of Earnings Components

Following Sloan (1996), I conduct the non-linear regression-based test (MISHIKIN, 1983). First, I run the Mishkin (1983) test for all sample and then for segregate subsamples of loss and profit firm, but not conditioned on the level of readability. This approach is based on a recursive system of two equations that tests the null hypothesis that the market rationally anticipates and prices the persistence of current earnings with respect to future earnings. The test compares the coefficients of the forecast equation with the coefficient of pricing equation, which are estimated simultaneously using a generalized nonlinear least squares estimation procedure:

$$Earn_{t+1} = \beta_0 + \beta_1 Earn_t + + \upsilon_{t+1} \tag{3.3}$$

$$R_{t+1} = \delta_0 + \delta_1 \left[Earn_{t+1} - \beta_0 - \beta_1^* Earn_t \right] + \varepsilon_{t+1} \tag{3.4}$$

where R_{t+1} is one-year-ahead size-adjusted returns, which is measured as annual size-adjusted buy-and-hold returns from the beginning of the next month after the 10-K is issued.

Equation (3.3) represents the forecast equation which is equal to equation (3.1). The β_1 is the persistence coefficient of current earnings for one-year-ahead earnings. On the other hand, equation (3.4) represents the pricing equation which uses abnormal returns to infer the implied persistence that investor assign to earnings persistence. β^*_1 refers to persistence of earnings, attributed by investor.

To test my second hypothesis I control in the forecast equation (3.5) and in the pricing equation (3.6) for the level of readability (high *versus* low) as following:

$$Earn_{t+1} = \alpha_0 + \alpha_1 Earn_t + \alpha_{1H} H\_Earn_t + \upsilon_{t+1} \tag{3.5}$$

$$R_{t+1} = \gamma_0 + \gamma_1 \left[Earn_{t+1} - \alpha_0 - \alpha^*_1 Earn_t - \alpha^*_{1H} H\_Earn_t \right] + \varepsilon_{t+1} \tag{3.6}$$

where α_1 represents the earnings persistence for firms with low level of FOG and α_{1H} represents the additional effect of firms with high level of FOG in terms of persistence. On the other hand, equation (3.6) represents the pricing equation which uses abnormal returns to infer the implied persistence that investor assign to earnings persistence. The α^*_1 coefficient refers to persistence of earnings, attributed by investor for firms with low level of FOG. The α^*_{1H} coefficient represents the persistence that investor assign to the additional effect of firms with high FOG.

I expect that the ratio of α_1 to α^*_1 is not different than one. In other words, I expect that investors price correctly the earnings persistence when they are faced on more readable information. On the other hand, I expect that the ratio of $(\alpha_1+\alpha_{1H})$ to $(\alpha^*_1+\alpha^*_{1H})$ is different than one, which means that investors mispricing earnings persistence for firms with less readable information. Consequently, I also expect that α_1/α^*_1 ratio is different than $(\alpha_1+\alpha_{1H})/(\alpha^*_1+\alpha^*_{1H})$, which means that investors price

differently firms with more readable information compared to firms with less readable information.

3.4 RESULTS

3.4.1 Descriptive Statistics

Table 16 Panel A presents descriptive statistics for full sample of the variables used in the models, Panel B presents statistics for firms with low FOG and high FOG, and Panel C presents statistics for loss and profit firms. Firms with more readable information have, on average, profit earnings, whereas firms with high FOG have, on average loss earnings. The difference related to FOG between firms with more readable information and firms with less readable information is around two and a half years. In other words, to understanding less readable MD&A section it is necessary for reader have 2.5 years of formal education more than to understanding more readable information.

As showed in Table 16 Panel C, loss firms have on average MD&A section with higher FOG than profit firms. The difference is around 0.5 years and it is statistically significant. This evidence corroborates with Li's (2008) results which find that annual reports of firms with lower earnings are harder to read.

TABLE 16: DESCRIPTIVE STATISTICS

Panel A: Full Sample

Variable	N	Mean	SD	Q1	Median	Q3
ARET $_{t+1}$	32338	0.024	0.582	-0.290	-0.050	0.205
EARN $_{t+1}$	32338	-0.019	0.191	-0.023	0.024	0.068
EARN $_{t}$	32338	-0.018	0.190	-0.021	0.025	0.069
FOG $_{t}$	32338	18.057	1.630	16.907	17.939	19.094

Panel B: L_FOG firms vs H_FOG Firms

	L_Fog (N = 16,169)		H_Fog (N = 16,169)		L_FOG - H_FOG		
Variable	Mean	Median	Mean	Median	Diff. in mean		t-statistics
ARET $_{t+1}$	0.031	-0.046	0.018	-0.054	0.013	**	(1.99)
EARN $_{t+1}$	0.005	0.029	-0.043	0.020	0.049	***	(23.07)
EARN $_{t}$	0.009	0.030	-0.046	0.019	0.055	***	(26.02)
FOG $_{t}$	16.761	16.907	19.353	19.094	-2.591	***	(-235.82)

Panel C: FOG Profit firms vs Loss Firms

	Loss Firms (N = 10,072)		Profit Firms (N = 22,266)		Loss - Profit	
Variable	Mean	Median	Mean	Median	Diff. in mean	t-statistics
FOG	18.344	18.250	17.927	17.800	0.417	(21.45)

Variable definitions: *EARN* is net income before extraordinary items scaled by average total assets; *ARET* is the abnormal return measured as annual size-adjusted buy-and-hold returns from the beginning of the next month after the 10-K is published. *FOG* is the Fog index calculated as (word per sentence + percent of complex words)*0.4. L_FOG are firms with FOG below the median; H_FOG are firms with FOG above the median.

3.4.2 Persistence of Earnings

Table 17 provides the results of estimating models related to earnings persistence for full, loss and profit samples. As demonstrated on prior research (SLOAN, 1996) the persistence of current earnings is, on average, 0.75. For loss firms the persistence (0.74) is quite similar to the full sample. However, for profit

firms, the earnings persistence is 0.65, suggesting that losses are more persistent than profits.

TABLE 17: PERSISTENCE OF EARNINGS PARAMETERS

$$Earn_{t+1} = \beta_0 + \beta_1 Earn_t + \upsilon_{t+1}$$

	Full Sample			Loss Sample			Profit Sample		
	Coeff.Est		(t-stat)	Coeff.Est		(t-stat)	Coeff.Est		(t-stat)
Intercept	-0.005	***	(-7.68)	-0.010	***	(-4.12)	0.002	***	(2.76)
β1	0.746	***	(200.30)	0.741	***	(94.17)	0.653	***	(68.80)
N	31,105			10,072			22,266		
Adj. R2	0.514			0.468			0.175		

Variable definitions: *EARN* is net income before extraordinary items scaled by average total assets.

***/**/* means significance at 0.01, 0.05 and 0.10 level, respectively.

Table 18 provides results for loss and profit firms controlling for the readability level. As predict on hypothesis H1, loss firms which have less readable MD&A section are associated with losses more persistent (0.653 + 0.114 = 0.767), whereas loss firms with more readable information have 0.653 of earnings persistence. In other words, loss firms with transitory losses write their MD&A sections in a more readable way than loss firms with persistent losses. On the other hand, profit firms with more readable MD&A section are associated with profits more persistent (0.723), whereas profit firms with less readable information have 0.569 (0.723 – 0.154). In other words, profit firms with transitory profits write their MD&A sections in a less readable way than profit firms with persistent profits. These evidence are similar to Li's (2008) results, although Li's (2008) results are not statistically significant for loss firms.

TABLE 18: PERSISTENCE OF EARNINGS PARAMETERS CONDITIONED ON THE READABILITY LEVEL

$$Earn_{t+1} = \alpha_0 + \alpha_{0H}H_t + \alpha_1 Earn_t + \alpha_{1H}H\_Earn_t + \upsilon_{t+1}$$

	Loss Sample			Profit Sample		
	Coeff.Est		(t-stat)	Coeff.Est		(t-stat)
Intercept	-0.012	***	(-3.35)	-0.001		(-1.03)
α_{0H}	0.000		(-0.03)	0.008	***	(4.50)
α_1	0.653	***	(44.43)	0.723	***	(56.21)
α_{1H}	0.114	***	(6.49)	-0.154	***	(-8.10)
N	10,072			22,266		
Adj. R2	0.472			0.178		

Variable definitions: *EARN* is net income before extraordinary items scaled by average total assets; *H* is an indicator variable equals one if FOG is high and zero otherwise; *H_Earn* is an interaction term between *H* and *EARN* variables.

***/**/* means significance at 0.01, 0.05 and 0.10 level, respectively.

3.4.3 Market Pricing of Earnings

Table 19 provides the results of Mishkin (1983) test for total earnings. For the full sample the market's perception of earnings persistence (β_1^*) is 0.767 and the difference for earnings persistence (β_1) is not statistically significant (*p-value* = 0.1626). Although the earnings persistence for profit firms (β_1= 0.653) is lower than for the full sample, investors price correctly (β_1^*=0.653) current earnings persistence. However, for loss firms there evidence suggests that investors do not perceive earnings persistence correctly. The difference between the earnings persistence coefficient (β_1= 0.741) and the market's perception coefficient (β_1^*=0.655) is significantly different (*p-value* = 0.0039). In other words investors understate the persistence of current earnings for loss firms.

TABLE 19: MISHIKIN TESTS OF EQUALITY OF PERCEIVED AND FORECASTING PARAMETERS

Forecast Equation: $Earn_{t+1} = \beta_0 + \beta_1 Earn_t + \upsilon_{t+1}$

Pricing Equation: $ARet_{+1} = \delta_0 + \delta_1 [Earn_{t+1} - \beta_0 - \beta_{1*} Earn_t] + z_{t+1}$

	Full Sample (N = 32,338)			Loss firms (N = 10,072)			Profit firms (N = 22,266)		
	Coeff.Est.		(t-stat)	Coeff.Est.		(t-stat)	Coeff.Est.		(t-stat)
β_1	0.746	***	(200.13)	0.741	***	(94.10)	0.653	***	(68.79)
β_{1*}	0.767	***	(53.94)	0.655	***	(22.44)	0.675	***	(18.12)
β_1 / β_{1*}	0.97			1.13			0.97		

Test of market efficiency for full sample:

cannot reject $\beta_1 = \beta_{1*}$: p-value = 0.1626

Test of market efficiency for loss sample:

reject $\beta_1 = \beta_{1*}$: p-value = 0.0039

Test of market efficiency for profit sample:

cannot reject $\beta_1 = \beta_{1*}$: p-value = 0.5696

Variable definitions: *EARN* is net income before extraordinary items scaled by average total assets; *ARET* is the abnormal return measured as annual size-adjusted buy-and-hold returns from the beginning of the next month after the 10-K is published.

***/**/* means significance at 0.01, 0.05 and 0.10 level, respectively.

Table 20 provides the results of Mishkin (1983) test for total earnings, but controlled for the level of readability for both loss and profit firms. As predicted in hypothesis H2, the level of readability influences the market's perception of current earnings persistence for loss profit. Firms with low FOG and negative earnings have on average earnings persistence (α_1) of 0.653. The estimate of the market's perceived earnings persistence (α_1^*) is 0.693, which is not statistically different (p-value = 0.4398) for the real value. Therefore, investors price correctly the current earnings persistence for loss firms when they are faced on more readable

information. Firms with high FOG and negative earnings have on average earnings persistence ($\alpha_1 + \alpha_{1H}$) of 0.767. Differently for loss firms with more readable information, the market's perception of earnings persistence ($\alpha_1^*+\alpha_{1H}^*$=0.693 – 0.050=0.643) is lower and statistically different from the true value (p-value = 0.0001). In other word, investors understate the current earnings persistence for loss firms with less readable information. Moreover, the ratio of ($\alpha_1 + \alpha_{1H}$) to ($\alpha_1^*+\alpha_{1H}^*$) is significantly greater than the ratio of α_1 to α_1^*, indicating that there are significant differences in the efficient pricing of current earnings across the low FOG and high FOG subsamples for loss firms.

For profit firms the hypothesis H2 is not confirmed. Firms with low FOG and positive earnings have on average earnings persistence (α_1) of 0.693. The estimate of the market's perceived earnings persistence (α_1^*) is 0.686, which is not statistically different (p-value = 0.8743) for the real value. Therefore, as for loss firms, investors price correctly the current earnings persistence of profit firms when they are faced on more readable information. Firms with high FOG and positive earnings have on average earnings persistence ($\alpha_1 + \alpha_{1H}$) of 0.602. Similar of profit firms with more readable information, the market's perception of earnings persistence ($\alpha_1^*+\alpha_{1H}^*$=0.686 – 0.091=0.595) is right and it is not statistically different from the true value (p-value = 0.2241). In other word, investors price correctly the current earnings persistence independent if information is less or more readable. Moreover, the ratio of ($\alpha_1 + \alpha_{1H}$) to ($\alpha_1^*+\alpha_{1H}^*$) is not significantly different than the ratio of α_1 to α_1^*, indicating that there are not significant differences in the efficient pricing of current earnings across the low FOG and high FOG subsamples for profit firms.

TABLE 20: MISHIKIN TESTS OF EQUALITY OF PERCEIVED AND FORECASTING PARAMETERS CONDITIONED ON THE LEVEL OF READABILITY

Forecast Equation: $Earn_{t+1} = \alpha_0 + \alpha_1 Earn_t + \alpha_{1H} H\_Earn_t + \upsilon_{t+1}$

Pricing Equation: $ARet_{+1} = \gamma_0 + \gamma_1 [Earn_{t+1} - \alpha_0 - \alpha 1 * Earn_t - \alpha_{1H} * H\_Earn_t] + \varepsilon_{t+1}$

	Loss firms L_Fog vs H_Fog (N = 10,072)			Profit firms L_Fog vs H_Fog (N = 22,266)		
	Coeff.Est.		(t-stat)	Coeff.Est.		(t-stat)
α_1	0.653	***	(49.61)	0.693	***	(62.81)
α_{1*}	0.693	***	(14.19)	0.686	***	(15.84)
α_{1H}	0.114	***	(8.34)	-0.091	***	(-7.09)
α_{1H*}	-0.050		(-0.97)	-0.025		(-0.50)
α_1/α_{1*}	0.94			1.01		
$(\alpha_1+\alpha_{1H})/(\alpha_{1*}+\alpha_{1H*})$	1.19			0.91		

Test of market efficiency for loss firms:

Equality of eanings parameters across equation for low FOG (i.e., 0.94 different from 1?)

cannot reject $\alpha_1 = \alpha_{1*}$: p-value = 0.4398

Equality of eanings parameters across equation for high FOG (i.e., 1.19 different from 1?)

reject $(\alpha_1+\alpha_{1H}) = (\alpha_{1*}+\alpha_{1H*})$: p-value = 0.0001

Difference in market efficiency ratios low FOG vs high FOG (i.e., 094 different from 1.19?)

reject $\alpha_1/\alpha_{1*} = (\alpha_1+\alpha_{1H})/(\alpha_{1*}+\alpha_{1H*})$: p-value = 0.0041

Test of market efficiency for profit firms:

Equality of eanings parameters across equation for low FOG (i.e., 1.01 different from 1?)

cannot reject $\alpha_1 = \alpha_{1*}$: p-value = 0.8743

Equality of eanings parameters across equation for high FOG (i.e., 0.91 different from 1?)

cannot reject $(\alpha_1+\alpha_{1H}) = (\alpha_{1*}+\alpha_{1H*})$: p-value = 0.2241

Difference in market efficiency ratios low FOG vs high FOG (i.e., 1.01 different from 0.91?)

cannot reject $\alpha_1/\alpha_{1*} = (\alpha_1+\alpha_{1H})/(\alpha_{1*}+\alpha_{1H*})$: p-value = 0.1959

Variable definitions: *EARN* is net income before extraordinary items scaled by average total assets; H is an indicator variable equals one if FOG is high and zero otherwise; H_Earn is an interaction term between H and EARN variables; *ARET* is the abnormal return measured as annual size-adjusted buy-and-hold returns from the beginning of the next month after the 10-K is published.

***/**/* means significance at 0.01, 0.05 and 0.10 level, respectively.

3.5 CONCLUSION

This paper provides evidence that managers use strategically corporate disclosure activity in order to mislead or to influence the investors' understanding about firms' earnings persistence. I use the Mishikin (1983) test to analyze whether investors expectations are correctly associated to the real value of firms' earnings persistence conditioned on different levels of difficulty to read and understand the MD&A section. Results show that the level of readability influences the process of pricing current earnings by investors, at least for firms with negative earnings. Specifically, for loss firms market understates the earnings persistence when they are faced on less readable information. In other words market estimates that losses are more transitory than they really are. For profit firms I do not find evidence that market is influenced by "foggier" information. Investors understand even for less readable MD&A section the earnings persistence and pricing correctly in both cases for firms with low FOG and for firms with high FOG.

Some different possible explanations can be associated to different results for loss and profit firms. First, as showed on descriptive analysis the "foggier" firms have on average negative earnings, whereas firms with more readable information have on average positive earnings. Additionally, loss firms have on average MD&A section less readable than profit firms. Therefore, assuming all others things equal it is expect that the effect of "foggier" firms is more pronounced for loss firms than for profit firms. Another possible explanation, but not investigate by this paper, is that perhaps sophisticated investors who are able to better understanding less readable information can be concentrated on profit firms.

Future research can follow three paths. First, analyze whether is possible to gain abnormal return using a trading strategy based on the readability level of information. Second, researchers can explore the earnings components as accruals and cash flow to identify whether the level of readability is more related with one or other component. Finally, as a complementary analysis future research can related the level of readability with investor sophistication and looking for even sophisticated investors are affected by the readability level of information.

CONCLUSION

This dissertation provides evidence about determinants and consequences of readability of Management Discussion and Analysis. Using the Fog index in all three papers as proxy for readability I investigate whether the level of readability is influenced by the level of earnings management and whether the level of readability helps to predict misstating firm. Additionally, I also investigated the impact of readability on the investors' perception about earnings persistence.

Overall, my results suggest that the readability is subject to managers' discretion. In other words, managers can manipulate the writing making it easy or difficult understanding according to their incentives. I provide evidence that firms which engaging in earnings management practices to meet or beat the last-earnings benchmark, use strategic corporate disclosure activities in order to hide the path taken to achieve their goals. I also show evidence that the level of readability can help to predict misstating firms. My results suggest that after controlling for other misstatements determinants as financial statements variables, off-balance-sheet variables and market-related variables, the readability increase the probability to detect a misstatement event. Based on F-score and sensitivity analysis proposed by Dechow et al. (2011), I find evidence that models which include the Fog index as a proxy for readability present a slight better performance than models without readability. Finally, my results also provide evidence that managers use strategically corporate disclosure activity in order to mislead or to influence the investors' understanding about firms' earnings persistence. Specifically, for loss firms market understates the earnings persistence when they are faced on less readable information. In other words market estimates that losses are more transitory than they really are.

Results of my dissertation contribute to accounting literature in different ways. First, I extend the results associated with determinants of readability of MD&A section. This is the first paper which explore alternative explanation proposed by Bloomfield (2008) related to type of news and readability. I show that the readability can not be explained only by ontological questions, but other factors as earnings management help to understand the variability on the readability.

Second, I improve models which help to predict misstating firms. More specifically, I add a new dimension on Dechow et al. (2011) models related to readability which increases the likelihood to detect an AAER firm. Therefore my results provide insights to financial statement users, especially to investors, auditors and regulators, about a new characteristic of misstating firm.

Third, my results add new evidence related to earnings persistence literature. I show evidence that investor are not able to identify correctly the earnings persistence for loss firm with harder readability. Therefore, readability could be one possible explanation for earnings and their components anomalies.

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