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MANAGEMENT REPORTING COMPLEXITY AND CONTENT RELATION TO EARNINGS MANAGEMENT: EVIDENCE FROM THE BALTICS

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Management Reporting Complexity and Content Relation to Earnings Management: Evidence from the Baltics

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Abstract

Building on the findings on report readability and linguistic features' relation to earnings management/firm performance by Lo et al. (2017) and Li (2008), this paper explores how management discussion and analysis text complexity and content relate to earnings management in the Baltic states. We base our analysis on a panel data set consisting of 250 firm-years from 2012 to 2016, use Fog and Flesch indices as the main indicators of reporting readability and explore such language features as relative frequencies of self-referential, positive emotion, future focus words and causation words. For proxying earnings management we use the modified Jones model (Dechow et al., 1995) that captures discretionary accruals earnings management, a proxy for real earnings management, and the combination of both. We find that there is a positive relationship between earnings management and complexity only for liquid companies, which might be so due to increased strategic reporting incentives for them. We do not find robust relationships between language features and earnings management, possibly due to lack of systematic usage of such features, different features than the ones we examine being used by managers, or the psychological reasons for using specific features being different in the context of hiding earnings management.

Keywords: earnings management, management obfuscation hypothesis, annual report readability, reporting complexity, language features, Baltic states

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1. Introduction

The existing accounting standards provide rules and guidance on how firms have to report financial performance. However, management still has some discretion in deciding how to present financial information. Hence, there is a possibility to misrepresent the true financials to either mislead investors who use that information or to achieve favourable contractual outcomes that depend on a firm's reported financial performance. Spotting earnings management is difficult from the outside, however, earnings management research uses relationship between accruals, earnings and underlying cash flows or time series properties of earnings to spot cases when earnings management could be taking place. In recent years these methods have been complemented by an analysis of the linguistic features of a company's annual report text.

The "management obfuscation hypothesis" implies that companies who manage earnings have annual reports that are intentionally written to be more difficult to comprehend in order to hide earnings management from investors. This hypothesis has been confirmed to be true in a recent paper by Lo, Ramos, & Rogo (2017). Also, Li (2008) has found that companies who have worse and less persistent financial results have annual reports that are harder to read and that firms who have less persistent earnings have more causation words, less positive emotion words, and more future tense verbs in their management discussion and analysis (MD&A) text.

However, the studies on the relationship between linguistic features of annual reports and firm financials/earnings management have been carried out mostly using samples of United States companies. To the best of our knowledge, this approach has not yet been widely utilized to examine if such relationships exist in European companies as well. We have chosen to examine the relationship between earnings management and reporting complexity and content in the Baltic states since it is a rather undeveloped, different and new capital market compared to the United States. Performing this kind of analysis sheds a light on similarities or differences in how managers in the Baltics, who have to adhere to different accounting guidelines than managers in the United States (IFRS vs GAAP, respectively), use accounting numbers and annual report text to possibly obfuscate bad financial performance. In fact, previous research has found that under US GAAP firms exhibit less earnings management than under IFRS (e.g., Lin, Riccardi, & Wang, 2012; Goncharov & Zimmermann, 2007). Also, previous research on the subject has established links between complexity and earnings management and earnings persistence, but the link between other linguistic features (e.g., the aforementioned use of future tense verbs, causation words, etc.) and earnings management, to the best of our knowledge, has not yet been examined. The questions we answer are: (1) **how does management reporting complexity relate to earnings management in the Baltic states?** and (2) **how does management reporting content (i.e. language features) relate to earnings management in the Baltic states?**

The examination is performed using a panel data set of 250 firm-year observations in the period 2012-2016. We manually retrieve and compile plain text files from companies' annual reports and measure text complexity using Fog and Flesch indices. To measure specific language feature usage in the text, we look at relative frequencies of self-referential ("I", "we"), positive emotion (e.g., "love", "nice", "sweet"), future focus words (e.g., "may", "will", "soon") and causation words (e.g., "because", "effect"). We use the modified Jones model (Dechow et al., 1995) that captures discretionary accruals earnings management, a proxy for real earnings management, and the combination of both to spot and measure possible earnings management. Afterwards, we perform the following regressions to answer each of our research questions – one with Fog/Flesch index as the dependent variable and one with each of the four language features as the dependent variable, using earnings management proxies and control variables as the explanatory variables.

Our results show that Baltic listed companies exhibit a somewhat different relationship between earnings management and reporting complexity than found in the United States samples – in the market overall there is no significant relationship between earnings management and readability, but it becomes significantly positive for a subsample of more liquid companies. We do not find strong evidence that the categories of language tools we examine are related to earnings management.

We believe that the results obtained during the research are useful in a number of ways. First of all, they show if size of the market or stage of market development, as well as accounting standards, might influence whether the management obfuscation hypothesis still holds, which advances the theoretical understanding of this concept and provides new directions for its further exploration. The results are useful to regulators and investors in the Baltic companies since knowledge about how reporting complexity and content are related to earnings management can help to decide if linguistics of annual reports could be used to better spot that earnings are being managed in companies from the outside (in addition to looking at financials of companies). Also, this analysis of reporting complexity of Baltic companies is useful to regulatory authorities in the Baltic states to see if some complexity-reducing initiatives with regard to annual report text need to be established since it has been shown by previous research that difficult-to-understand company filings are related to less trading by small investors and overall (Miller, 2010), which can hinder the development of these relatively new markets and diminish their liquidity.

The paper is organized as follows. Section 2 is the literature review, where we discuss previous findings on earnings management and firm financials relation to linguistic features of annual report text. It is followed by Section 3 where we lay out our methodology for answering the research questions. In Section 4 we describe our findings, and in Section 5 we discuss them. Finally, Section 6 concludes.

2. Literature Review

2.1. Brief overview of research on earnings management

Earnings management practices in the literature are usually classified into two categories: accruals management and real earnings management, i.e. taking real economic actions and affecting actual cash flows (Lo, 2008). Authors have looked at the most appropriate ways how to spot it, e.g., Dechow, Sloan, and Sweeney (1995) have discovered that various accruals-based models[1] produce reasonably good results for a random sample of event-years, however, their power is low for discovering earnings management of realistically possible magnitudes and they point to earnings management for firms with extreme cash flow from operations or earnings performance. Hence, Dechow et al. (1995) highlight the importance of controlling for financial performance when researching earnings management. Other authors have looked at the motivations for managing earnings, for instance, Graham, Harvey, and Rajgopal (2005) have discovered that managers would better try to take real economic actions, such as passing on positive NPV projects, delaying maintenance or cutting advertising expenses (i.e. sacrificing long term value) just to meet or beat the earnings benchmark rather than by manipulating the accounting numbers, thus highlighting the need to examine possibility of real earnings management within companies in addition to accruals management. Besides that, research has also been made on the tools and techniques used to achieve the desired effects on reported earnings numbers (e.g., Nelson, Elliott, & Tarpley, 2002), on the strength of internal governance in companies to prevent it (e.g., Cheng, Lee, & Shevlin, 2016), on how managers trade off accruals and real activities earnings management (e.g., Zang, 2012), etc.

2.2. Previous research on relation between firm financials and reporting complexity

Readability of companies' information disclosures has been examined for quite a long time already. For instance, Jones (1988) looked at a UK company's annual report readability from 1952 to 1985 and found that texts have become more difficult to read over time as well as that the company's turnover is negatively related with text readability. The same trend in readability over time has been shown by Soper and Dolphin (1964) and Barnett and Leoffler (1979) when

[1] Dechow et al. (1995) tested Healy Model, DeAngelo Model, Jones Model, Modified Jones Model and Industry Model.

examining samples of United States companies. Smith and Smith (1971) analyzed readability of notes to financial statements of Fortune 50 companies in 1969 and found that complexity of notes limits understanding. In a large-sample study of more than 15,000 non-U.S. companies in 42 countries over the period of 1998-2011 Lang and Lawrence (2015) also found that over time annual report length and complexity have increased significantly. Overall, previous research is rather aligned in its findings that MD&A and notes in companies' annual reports are difficult to read and have become more and more so over time.

In recent years, more attention than before has been paid to examining how report readability relates to firm financials. A paper by Vargas, Almeida, and Junior (2014) has examined how MD&A part, and specifically reporting on income, differs in profit and loss periods in Brazilian market and has found that in periods of loss, the part in the reports designated for discussing income is shorter, the overall length of reports is similar, but there is more emphasis on discussing gross margin, EBITDA and other positive results, and more financial terms are used to divert readers' attention, instead of addressing the negative aspects of performance. Similar trends have been also found in Indian market by examining automobile companies' MD&A texts during the global financial crisis, where it has been found that complexity of reporting increased, implying that obfuscation appears not only to hide bad performance, but also due to tough external environment (Srinivasan, Srinivasan, & Marques, 2017). In Australian market, it has been found that chairman's/CEO's reports in Australian listed companies have low readability levels and that there is a relationship between changes in net income and obfuscation (Bayerlein, 2010). All in all, non-U.S. market studies show that annual reports or parts of them are difficult to read and that managers try to obfuscate bad performance or divert readers' attention from it.

Li (2008) has examined the relationship between annual report readability and firms' financial performance and its persistence in the United States, as well as looked at the language features that are more characteristic in the reports of firms whose earnings are not persistent. He confirms his "management obfuscation hypothesis" that managers of companies whose financial results are not positive tend to write longer and more difficult reports to hide and mitigate the negative effect on stock returns. This hypothesis is based on the "incomplete revelation hypothesis" developed by Bloomfield (2002). The idea is that managers report strategically since in efficient markets investors will only incur costs of analysing data until the point when they equal return from doing that (Grossman and Stiglitz, 1980; Bloomfield, 2002). So, according to the incomplete revelation hypothesis, if managers want to delay the effect that unpleasant disclosures of information might have on their company's stock price or make it smaller in magnitude, they can make analysis of bad news more costly by writing less transparent, more difficult and longer annual reports (Li, 2008; Bloomfield, 2002). In general, Li (2008) finds support for his hypothesis. In addition, he looks at language features of the reports (self-referential words, exclusive words, causation words, positive emotion words, and future tense verbs) and finds that profitable firms with lower level of earnings persistence have more causation words, less positive emotion words, and more future tense verbs in their MD&A text. In contrary, loss-generating companies who have less persistent earnings have more positive emotion words in their MD&A text. The reasoning Li (2008) puts forward for examining these language features is founded in psychology literature that has found that people who express untrue information communicate differently than people who tell the truth (e.g., Newman, Pennebaker, Berry, & Richards, 2003).

Bloomfield (2008) examines a couple of alternative explanations for Li's (2008) results besides obfuscation. For instance, it could be that worse financial results are inherently more difficult and lengthy to explain (ontology explanation), or that managers, as is proven to be true by psychology literature, tend to attribute positive results to skill and negative results to bad luck (Miller & Ross, 1975), so they might need more words and more complicated language to link those external events to a firm's performance (attribution explanation), or that managers might try to divert investors' attention from the bad performance information by writing about other positive things and future prospects, which would also entail additional length (misdirection explanation). The case study Bloomfield (2008) performs generally leans towards obfuscation hypothesis as the most likely explanation for changes in the analysed firm's reporting when their performance changed.

The purposeful obfuscation idea has been further taken to the test by Lo et al. (2017) who have examined the relationship between MD&A readability and earnings management. The authors pay attention to both obfuscation and ontology explanations that have been examined by Li (2008) and Bloomfield (2008), and it is done by examining firms that might have managed earnings upwards to meet or beat an earnings target, because in that case managers have a motive to try to hide the tools used to achieve that even though the news they communicate (about a reached earnings target) are positive. The authors find that purposeful obfuscation is the most appropriate explanation for the variation in readability levels of annual reports for firms that have likely engaged in managing earnings and suggest that managers try to make disclosures foggier to influence investors' perception of firm value and hide that underlying fundamentals differ from reported performance. More specifically, they find that there is no significant difference in the reporting length between firms who have likely managed earnings and those who have not, however, the former ones have more complex disclosures (as measured by Fog index), so these firms are not telling more to investors, they are simply communicating using more difficult language.

However, Courtis (2004), who defines obfuscation using a combination of low readability level and high readability variability of text, indicates that obfuscation might be present because of three reasons: (1) in order to reduce investor nervousness arising from the way that business environment impacts a company's performance, management purposefully writes in a non-transparent manner over time, (2) management purposely tries to obfuscate unpleasant information and give misleading description of the current situation and/or (3) obfuscation in texts appears because of lack of coordination between different people who write the report text and have varying writing capabilities/styles.

All in all, even though there exist alternative explanations for increased reporting complexity when a firm's financial situation deteriorates, the management obfuscation hypothesis seems to be true when examined on samples of United States companies.

2.3. Previous research on earnings management and report readability in the Baltics

To the best of our knowledge, earnings management and reporting complexity and content relation has not been examined in the Baltic states market. Also, the amount of previous research on earnings management and reporting complexity/style features is limited. A brief summary of papers in these two areas close to the topic of our paper can be found in Appendix A. Bistrova and Lace (2012) have examined the link between earnings quality and corporate governance quality in CEE companies; Grigorjeva and Lace (2008) have looked at whether earnings quality is reflected in stock prices; Garsva, Skuodas, and Rudzioniene (2012) have examined earnings management in European banks and discussed separately the results for banks in the Baltic states; and Roo (2011) has looked at linguistic features in annual report texts of Estonian publicly listed companies.

Overall, the amount of research on earnings management and reporting complexity/style in public companies in the Baltic states is quite limited, and often the number of companies included in the sample is small. Therefore, we feel that our findings can fill this existing research gap.

3. Methodology

3.1. Sample

The analysis is carried out on firms that were listed on Nasdaq OMX Baltic stock exchange during the five-year period from January 1, 2012, to December 31, 2016. Sample includes companies from both Baltic Main List and Baltic Secondary List. To avoid survivorship bias, we do not exclude firms that were delisted during this period or have been listed for less than the whole period. Therefore, the initial sample consists of 86 companies and 374 firm-years.

Due to differences in financial statements, financial firms were excluded from the sample. The total number of firm-years of financial firms sums up to 16. After subtracting these, the sample consists of 358 firm-years of 82 different companies. Besides that, 108 firm-years had to be excluded from the sample because the text of the annual report was not retrievable and/or data for financial proxies and control variables was not available, leaving us with a final sample of 250 firm-years of 58 different companies.

With respect to those firms that have been delisted or were not listed for all years of our sample period, we analyse only those firm-years when these firms have been listed. The reason for doing this is that during the years they have not been a publicly traded company, financial statements and annual reports attract less attention and are not relevant to investors and the general public, which quite significantly decreases the incentives to use strategic reporting tools in MD&A. See Appendix B for the list of all companies and number of firm-years included in the sample.

3.2. Earnings management proxies

To determine the possible level of earnings management within financial statements of Baltic companies, we use several proxies. The simplest indication of possible earnings management is obtained by noticing cases when a company's earnings per share (EPS) figure slightly beats or meets the EPS of the previous year. However, as pointed out by Lo et al. (2017), if used as the only measure this proxy could attribute earnings management to firms who have just met or beaten the target without managing their accounting numbers, so additional measures like discretionary accruals and real earnings management proxies are used. Then, as described in more detail in Section 3.5, these three types of proxies are combined using interaction terms to jointly test for the result of earnings management (as measured by the change in EPS) and two ways how it could have been achieved (managing accruals or doing real earnings management), which gives a more powerful test than using any of these proxies on a stand-alone basis.

3.2.1. Earnings per share (EPS). For earnings benchmark, as suggested by Lo et al. (2017), we use past year's earnings of a company (instead of analyst forecasts) since in the annual report Baltic companies would most often use it as a benchmark, given the fact that in the Baltics analyst following for companies is not as substantial and significant to believe that they would try to meet or beat analyst forecasts. More specifically, we look at EPS before extraordinary items since companies who just meet or slightly beat earnings benchmarks would be a suspect to having managed earnings (Lo et al., 2017). Variable *MBE* (short for "meeting or beating earnings") is assigned a value equal to 1 if ΔEPS is in the interval from zero to a small positive number (which is defined as either 1, 2, or 3 euro cents for increasing robustness of the tests), and 0 otherwise, similarly as done by Lo et al. (2017). Data about companies' EPS is extracted from Thomson Reuters Eikon.

3.2.2. Discretionary expenses. For real activities earnings management proxy we use a measure utilized by Lo et al. (2017), which they have borrowed from Roychowdhury (2006), where the proxy is constructed as the negative sum of change in R&D expenses and change in advertising expenses, which is then divided by opening total assets:

$$RAM_t = -(\Delta R\&D\ expense_t + \Delta Advertising\ expense_t)/\ TA_{t-1} \quad (1)$$

where RAM_t is real activities earnings management at the end of year t, $\Delta R\&D\ expense_t$ is the change in R&D expenses from year $t-1$ to t, $\Delta Advertising\ expense_t$ is change in advertising expenses from year $t-1$ to t, and TA_{t-1} are total assets at the end of year $t-1$. This measure proxies for real activity earnings management since these two types of expenses are usually considered to be among the easiest to cut, and management might choose to do so in order to increase earnings to meet a benchmark. Hence, the more these expenses are decreased, the larger is RAM_t value, and $RAM_t>0$ indicates possible real earnings management (Lo et al., 2017).
Since company financial statements are extracted from Thomson Reuters Eikon, the entries for firms' R&D and in many firm-years for advertising expenses are empty (for a reason unknown to us). Therefore, we take these entries from notes of each company's financial statements (as

shown in annual reports retrieved from NASDAQ OMX Baltic website) and, in the absence of such entries in companies' reported financial statements and/or notes to financial statements, we take it as a sign that no such expenses exist and assign a value of zero for that firm-year's R&D or advertising expenses.

3.2.3. Discretionary accruals. Dechow et al. (1995) found that their modification of the Jones model was able to provide the most powerful tests for detecting earnings management. Also, they found that this model (along with the original Jones model) had the lowest standard errors of all the models they tested, which indicates that this model is more effective than others and has smaller problems coming from omitted determinants of nondiscretionary accruals. Therefore, given the superiority of this accruals model and the fact that it was also used by Lo et al. (2017) in a study very similar to ours, we choose to employ the Modified Jones model from Dechow et al. (1995) in our tests. The model is specified as follows:

$$\frac{TotAccr_t}{TA_{t-1}} = \alpha_0 + \alpha_1\left(\frac{1}{TA_{t-1}}\right) + \alpha_2\left(\frac{\Delta Rev_t}{TA_{t-1}} - \frac{\Delta Rec_t}{TA_{t-1}}\right) + \alpha_3\left(\frac{PPE_t}{TA_{t-1}}\right) \tag{2}$$

where $TotAccr_t$ are total operating accruals at the end of year t (see Appendix D for the operating accruals formula we use), ΔRev_t is the change in revenues from year $t-1$ to t, ΔRec_t are net receivables in year t less net receivables in year $t-1$, PPE_t is gross property, plant, and equipment and the end of year t, and TA_{t-1} are total assets at the end of year $t-1$. The residuals from performing an OLS regression of this model are the discretionary accruals (*DA*). *DA*>0 indicates possible earnings management since the independent variables in the model explain the non-discretionary accruals part which is changing based on a firm's economic conditions (Dechow et al., 1995), and if the residual is positive, it shows that management has chosen to increase discretionary accruals (the part of accruals determined not by business situation, but at their discretion). This model is estimated on a cross-sectional basis, taking into account industry effects (as suggested by Lo et al., 2017). Necessary financial figures are retrieved from Thomson Reuters Eikon and, if missing, filled in manually using company annual reports.

3.3. Language complexity and content measures

The second part of our sampling and analysis is done with MD&A part text of the English language versions of annual reports of all the firm-years included in the sample (retrieved from NASDAQ OMX Baltic website). MD&A text is chosen for analysis because anecdotal evidence suggests that the two other parts of annual report text (description of accounting policies used by the company and notes to financial statements) in the Baltic markets is often very similar from year to year, hence, we only use MD&A part text as it is drafted each year to explain the particular year's results, challenges and future prospects, and thus should have more relation to changes in financial situation. We manually retrieve and compile plain text files from company annual reports' MD&A part, excluding any titles and unfinished sentences in order not to artificially simplify the text, as well as any tables/tabulated text since the readability formulas we apply are not meant for analysing such text.

3.3.1. Language complexity measures. For text complexity analysis we use four estimates: length of the annual report (logarithm of the number of pages in the annual report document, subtracting the number of pages of auditor's report), MD&A length (logarithm of number of words in the MD&A part), and computational linguistics measures called Gunning Fog Index (used, e.g., by Lo et al. (2017), Lang & Lawrence (2015), and Li (2008)) and Flesch Reading Ease Index (used, e.g., by Courtis (2004), and Barnett & Leoffler (1979)). The different complexity measures are used since each of them has its flaws[2], therefore, by testing earnings management relation to each of them, we increase the robustness of our conclusions and avoid them being dependent on one particular readability measure being chosen. Even though many readability formulas have been developed for measuring text complexity in various contexts, we choose to use Fog and Flesch indices due to their remaining popularity over the years, especially in research on related topics (e.g., by Li (2008), Lang & Lawrence (2015), and Lo et al (2017)),

[2] Courtis (2004) reviews previous research on readability formulas and points out the general concern with measuring text readability based on indices - they all attempt to predict what an actual person reading the text might say or what comprehension tests would show about its complexity. The precision of this prediction, however, depends on whether a formula is able to capture elements of the text that are related to understanding. Out of these elements, only the ones related to style have been found to be measurable, while leaving out other important elements that impact comprehension, such as content, style, format and organisation (Courtis, 1986). Also, as Courtis (1986) points out, readability formulas cannot take into account the reader's background and the concepts used in the text and they do not capture how motivational materials are and how new concepts are presented in them. They also cannot measure how logically and coherently the text has been arranged, how much abstraction there is, and other elements related to readability, such as graphic design, size of letters and their style, full pages of text, long paragraphs, punctuation, illustrations, etc. (Dreyer, 1984).

which indicates they could be used in this context and allows us to better compare our results and descriptive statistics to these previous studies.

Length, as Li (2008) argues, is used to measure readability ease because information in longer documents, *ceteris paribus*, could be considered to be more difficult and costly to process by investors and, therefore, managers could be purposefully making reports longer to hide information which they do not want to be understood easily. While length on its own might not be a very good measure of complexity (and might not necessarily cause it), it has been found that it is strongly correlated with complexity and is a simple measure to apply (Courtis, 2004).

The Gunning Fog Index takes the percent of complex words (defined as words with three syllables or more out of all words in the text), adds to that the average number of words per sentence (number of words divided by number of sentences in a text), and scales the sum by 0.4, giving a proxy for how many years of schooling a person with an average intelligence level would need to have to comprehend the text (for more details see Appendix C).

$$FOG = 0.4 * (words\ per\ sentence + percent\ of\ complex\ words) \tag{3}$$

Flesch Reading Ease Index measures readability on a 100 point scale (for more details see Appendix C) and is computed by the following method:

$$FLESCH = 206.835 - (1.015 \ * words\ per\ sentence) - (84.6 \ * syllables\ per\ word) \tag{4}$$

Higher index values, which will be achieved if there are shorter sentences with words that have less syllables, indicate better readability (Li, 2008).

To measure the values of these indices for MD&A text of the firm-years in our sample, we use Lingua::EN::Fathom package of Perl computing language[3] that is able to perform the necessary calculations automatically. The validity of this package has been tested by Li (2008), who compared its calculation results with other studies and manual calculations using selected text samples, finding that the average index values in the sample are similar to those of other studies and that index values calculated with Lingua::EN::Fathom differ from the ones obtained manually by less than 5% in the majority of cases, thus, validating the program's reliability.

3.3.2. Language content measures. To examine more thoroughly the language features that are characteristic to annual report texts and see if there is a relation between some of them and

[3] The package is available at http://search.cpan.org/dist/Lingua-EN-Fathom/lib/Lingua/EN/Fathom.pm

earnings management, we also use all firm-years included in the sample. The theoretical basis for doing this kind of research are findings in psychology literature which show that people communicate differently depending on whether they are being truthful or not and that often the properties of language and style of expression can give more information than the text itself (e.g., Newman et al., 2003).

For this part of textual analysis a software called Linguistic Inquiry and Word Count (Version LIWC2015; 2015) is used. This software is widely used in various fields when examining language features, and is able to compute the degree to which different categories of words are used within a text. The default version of LIWC2015 dictionary consists of more than 6400 words, word stems and emoticons[4].

We use similar four categories of words and formulas for calculating variables as in Li (2008) - self-referential words, causation words, positive emotion words, and future focus words[5] - because these features are based in human psychology and should carry on their relevance through time and across countries.

People use more first-person singular pronouns when they are being truthful (Newman et al., 2003). Therefore, we use the relative percentage of self-referential words calculated as:

$$IvsU = \ln\left(\frac{1 + Self}{1 + You + Other}\right) \tag{5}$$

where *Self* is the proportion of first-person pronouns (36 words in the LIWC dictionary), *You* is the proportion of second-person pronouns (30 words), and *Other* is the share of third-person pronouns (28 words).

As Li (2008) argues, when people are attempting to explain something, they should be using more causation words, and they should be trying to explain something more when they are trying to hide something. Therefore, *Cause*, the frequency of causation words (135 words, such as “because”, “effect”), as calculated by the software, is also used.

[4] The number of words in the dictionary and the other data and information about the LIWC2015 edition that follows in this section comes from manuals retrieved from https://liwc.wpengine.com/wp-content/uploads/2015/11/LIWC2015_LanguageManual.pdf and https://s3-us-west-2.amazonaws.com/downloads.liwc.net/LIWC2015_OperatorManual.pdf

[5] Li (2008) also uses the fifth category – relative frequency of exclusive words, but we choose not to examine it due to the fact that in the current LIWC version this category no longer exists and is included in a much broader group of words (differentiation words), which would make this measure quite noisy.

Newman et al. (2003) also discovered that, when telling the truth, people use more positive emotion words. The variable to measure that is calculated as:

$$PvsN = ln\left(\frac{1 + Posemo}{1 + Negemo}\right) \tag{6}$$

where *Posemo* is the share of words with positive emotional tone (620 words, such as "love", "nice", "sweet") and *Negemo* is the proportion of words with negative emotional tone (744 words, such as "hurt", "ugly", "nasty").

Li (2008) proposed that, when doing worse financially and hiding something, managers should be trying to divert readers' attention to the future and avoid discussing the unpleasant present. Therefore, they should be using more future focus words in that case. The variable for measuring that is calculated as:

$$FvsP = ln\left(\frac{1 + Future}{1 + Past + Present}\right) \tag{7}$$

where *Future* is the percentage of future focus words (97 words, such as "may", "will", "soon"), and *Past* (341 word, including "ago", "did", "talked") and *Present* (424 words, such as "today", "is", "now") are the shares of past and present focus words in the text, respectively[6].

3.4. Control variables

Even though our research focuses on examining the purposeful obfuscation claim, it is important to recognize and control for other factors besides management's strategic reporting that might have an impact on report readability to avoid an omitted variable bias. We base the set of our control variables on the ones used by Lo et al. (2017) and Li (2008), but make the necessary changes to adjust the list to characteristics of the Baltic market (see control variable descriptions in Appendix D). Industry fixed effects (using Fama-French 12 industry groups) and year fixed effects are also added as potential factors affecting the complexity of reporting.

[6] Li (2008) in his paper used only frequencies of past, present and future tense verbs, but in the LIWC2015 version that we are using these categories have been updated to broader and more inclusive categories of past, present and future focus words, which is why we use these broader categories instead, and it is the reason for the large differences in the number of words in the dictionary in these categories if compared to what Li (2008) reports.

3.5. Estimation models

To answer the first research question on how reporting complexity relates to earnings management, we follow analogous procedure to the one employed by Lo et al. (2017). Since earnings management is most likely done upwards, not downwards, we separate the firm-years with indication of positive earnings management. We create a dummy variable *PosEM(DA)* that is equal to 1 if discretionary accruals (*DA*) are positive and 0 otherwise. Likewise, we create a dummy variable *PosEM(RAM)* that is equal to 1 if real earnings management proxy (*RAM*) is a positive number and 0 otherwise. Also, we create the opposite variables *NegEM(DA)* and *NegEM(RAM)* in a similar fashion. Positive *DA* would be a signal of upwards earnings management since discretionary accruals would have been increased in that year, and positive *RAM* would be a signal that R&D and/or advertising expenses have been decreased during the year, which would indicate income-increasing real earnings management. Also, by combining both previously created indicator variables, we create variables *PosEM(Comb)=PosEM(DA)+PosEM(RAM)* and *NegEM(Comb)=NegEM(DA)+NegEM(RAM)*.

Then, to increase the power of our estimations, we create interaction terms between our earnings management proxies instead of using them separately. For example, we use interaction terms *MBE()*PosEM(DA)*, *MBE()*PosEM(RAM)* and *MBE()*PosEM(Comb)* as well as equivalent interaction terms with *NegEM()* in our analysis.

After that, using our readability measures as dependent variables and earnings management variables and control variables as independent variables, we perform a regression of the following general form (similarly as specified in Lo et al. (2017)):

$$Readability_{it} = \beta_0 + \beta_1 EM_{it} + \Sigma\beta_j Control_{j,it} + \varepsilon \tag{8}$$

where *Readability* is one of the text complexity measures we use, *EM* are earnings management proxies and *Control* stands for the set of control variables.

When turning to examine our second research question on the relation between earnings management and reporting content, we use a similar specification only with the difference that instead of readability measures, we now use the indices related to reporting style as dependent variables:

$$LangF_{it} = \beta_0 + \beta_1 EM_{it} + \Sigma\beta_j Control_{j,it} + \varepsilon \tag{9}$$

where *LangF* is one of the variables containing relative frequencies of words in the four categories and all other variables are defined the same as previously. To ensure that proposed model specifications used by previous researchers work well in our case and provide both unbiased and efficient estimates, we will examine four specifications: originally planned regression in levels using year and industry fixed effects as in Lo et al. (2017) and Li (2008), fixed effects model, random effects model, and estimation in first differences, and then decide on the best option to base our analysis on.

3.6. Additional test

Other researchers have found that there are differences in managers' motivations to manage earnings depending on analyst following, i.e. companies that are monitored more by the market exhibit less earnings management (e.g., Yu, 2008). It has been also found that less liquid companies tend to have worse report readability (Lang & Lawrence, 2015). Considering that there are companies in the Baltic stock market with various liquidity levels, we hypothesize that there could be differences between liquid and less liquid company manager incentives to manage earnings and strategically report on their performance. It might be the same as in the US market (Yu, 2008) with more followed (in the case of the Baltics - more liquid) companies managing earnings less. Additionally, it could be that for the more liquid companies investor opinions on their earnings performance are more important and hence also the bad impact on share price in case investors notice earnings management and sell shares would be more likely to occur, hence they would have more incentives to strategically report. We, therefore, choose to perform an additional test to see if for the more liquid companies the relationship between earnings management and readability is stronger/larger in terms of magnitude by using a dataset compiled by Razums and Vitols (2017), and match their sample, which mainly consists of companies in Baltic Main list and the ones that are the most liquid[7], with our sample, and perform our model estimations for the subset of most liquid companies (this subset consists of 145 firm-years of 31

[7] To select the most liquid stocks, the authors calculated proportion of zero-trading days (defined as days in which opening and closing prices are equal, i.e. daily returns are zero) for each stock in the Baltic stock market listed on Main and Secondary List (similarly as us not excluding delisted companies) in the period 2010-2016, and due to the fact that this measure might misclassify days in which the same amount (or close to the same amount) of shares were bought and sold during the day resulting in zero return for the stock (even though there has been trading activity), they choose 40% zero-trading days as a threshold below which companies are considered liquid.

companies). Also, we try another more simplified way to check if the relationship differs for more liquid firm-years by estimating our model for the firm-years that are under the median value of stock return volatility variable *RetVol* (a subset of 125 firm-years; *RetVol* defined in Appendix D).

4. Results

4.1. Descriptive statistics

There are 124 firm-years (49.60%) from companies in the Main List, and 126 firm-years (50.40%) from companies in the Secondary List in our sample. There are 65 firm-years (26.00%) of Estonian companies, 88 firm-years (35.20%) of Lithuanian companies and 97 firm-years (38.80%) of Latvian companies. In terms of the financial years included in the sample, 20.40% of observations are from year 2012, 20.80% from 2013, 20.80% from 2014, 19.20% from 2015, and 18.80% from 2016. Therefore, we can say that the composition of our sample is rather balanced along all of these dimensions.

However, the division between industries in our sample is not as even. Most of the firm-years (31.2%) represent Fama-French industry group 1 (consumer non-durables), followed by group 12 (other) with 16.8%, group 3 (manufacturing) with 13.2%, and group 9 (shops, wholesale, retail) with 12.0% (see Table 1).

Table 1. Sample division between industries (using Fama-French 12 industry classification).

Industry code and description	**Frequency**	**Percent**
1 - Consumer Nondurables (Food, Tobacco, Textiles, Apparel, Leather, Toys)	78	31.2
2 - Consumer Durables (Cars, TVs, Furniture, Household Appliances)	12	4.8
3 - Manufacturing (Machinery, Trucks, Planes, Off Furn, Paper, Com Printing)	33	13.2
6 - Business Equipment (Computers, Software, and Electronic Equipment)	18	7.2
7 - Telephone and Television Transmission	5	2.0
8 - Utilities	7	2.8
9 - Wholesale, Retail, and Some Services (Laundries, Repair Shops)	30	12.0
10 - Healthcare, Medical Equipment, and Drugs	17	6.8
11 - Finance[8]	8	3.2
12 - Other (Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment)	42	16.8
Total	**250**	**100.0**

Descriptive statistics for the variables we use in our regressions for the full sample can be seen in Table 2. Both Fog and Flesch indices classify Baltic company MD&A texts as “difficult” on average (see Table 2 and Appendix C), which is only one category below results obtained by Lo et al. (2017) and Li (2008) that classified the texts as “unreadable” in their United States

[8] SIC codes obtained from Orbis database classify two companies in finance industry (using Fama-French 12 industry classification), however, they are kept in the sample because both of them are property/real estate development companies whose financial statement structure is the same as for all other companies in the sample.

company samples. Also, interestingly, the average change in EPS is -2 euro cents (so on average during the sample period there was a year-on-year decrease in EPS).

Table 2. Descriptive statistics for the main dependent and independent variables, full sample.

Variable	N	min	mean	median	max	st. dev.
ΔEPS	250	-6.04	-0.0213	0.00	6.69	0.968
RAM	250	-0.0813	0.000500	-0.000012	0.0564	0.0111
DA	250	-0.262	0.00	0.00	0.218	0.0726
Earnings	250	-0.307	0.0606	0.0498	0.403	0.0877
ln(pages)	250	2.94	4.07	4.26	5.24	0.593
ln(MDA words)	250	5.48	7.79	8.03	9.97	1.23
Fog	250	11.8	17.3	17.3	29.1	2.19
Flesch	250	2.53	33.0	32.3	53.2	7.14
IvsU	250	-0.554	-0.0506	-0.0677	1.04	0.281
cause	250	0.780	2.46	2.29	5.41	0.914
PvsN	250	-0.362	0.789	0.826	1.43	0.295
FvsP	250	-2.14	-1.50	-1.49	-0.738	0.228
Loss	250	0.00	0.18	0.00	1.00	0.385
Size	250	5.48	9.64	9.63	13.3	1.94
Age	250	4.00	33.6	21.0	150	33.2
MTB	250	0.350	0.969	0.872	2.71	0.445
RetVol	250	0.0179	0.194	0.0830	19.7	1.24
EarnVol	250	0.00397	0.0595	0.0382	0.315	0.0603
NBSeg	250	0.00	1.14	1.10	2.56	0.570
NGSeg	250	0.00	1.31	1.39	3.37	0.802

ΔEPS is the change in earnings per share; *RAM* is the real activities earnings management proxy; *DA* is discretionary accruals earnings management proxy, *Earnings* is a ratio of a company's operating earnings divided by opening total assets; *ln(pages)* is the logarithm of number of pages in annual report, excluding auditor's report; *ln(MDA words)* is the logarithm of number of words in our MD&A part text sample; *Fog* and *Flesch* are text readability indices; *IvsU* is the relative frequency of self-referential words; *cause* is the frequency of causation words; *PvsN* is the relative frequency of positive emotion words, and *FvsP* is the relative frequency of future focus words; *Loss* equals 1 if *Earnings* is <0, and equals 0 otherwise; *Size* is the logarithm of market value at the end of the fiscal year; *Age* shows the number of years since incorporation; *MTB* is the market-to-book ratio of assets; *RetVol* is monthly stock return standard deviation in the previous year, and *EarnVol* is the operating earnings (deflated by total assets) standard deviation in the previous five years; *NBSeg* and *NGSeg* show the logarithm of number of business and geographic segments, respectively.

When looking at the prevalence of possible earnings management in the sample (see Table 3), one can see that with the simple *MBE()* proxies the proportion of firm-years in which earnings are likely to have been managed ranges from 10.8% to 18.4% depending on the specification of the variable. The more refined proxies which are constructed as interaction terms between *MBE()* and *PosEM()* variables show that positive earnings management might have happened in 6.0% to 10.8% of firm-years, but the proportion of firm-years in which companies have met or beaten past years' earnings by zero to three cents, but have no suspected upwards earnings management (shown by *MBE()* interactions with *NegEM()*) is 4.4% to 8.8%. This positive earnings management share is considerably lower than the one reported by Bistrova and Lace (2012), but since the sample periods do not overlap, it is hard to tell if the difference comes from differences in estimation methods or changes in the market over time.

Table 3. Summary statistics for the variables used to proxy for earnings management.

Variable	Obs	Mean	Std.Dev.	Min	Max
MBE(1)	250	0.108	0.311	0	1
MBE(2)	250	0.160	0.367	0	1
MBE(3)	250	0.184	0.388	0	1
PosEM(RAM)	250	0.460	0.499	0	1
NegEM(RAM)	250	0.512	0.501	0	1
PosEM(DA)	250	0.480	0.501	0	1
NegEM(DA)	250	0.516	0.501	0	1
PosEM(Comb)	250	0.940	0.706	0	2
NegEM(Comb)	250	1.03	0.702	0	2
MBE(1) x PosEM(RAM)	250	0.06	0.238	0	1
MBE(2) x PosEM(RAM)	250	0.092	0.290	0	1
MBE(3) x PosEM(RAM)	250	0.108	0.311	0	1
MBE(1) x NegEM(RAM)	250	0.044	0.206	0	1
MBE(2) x NegEM(RAM)	250	0.064	0.245	0	1
MBE(3) x NegEM(RAM)	250	0.072	0.259	0	1
MBE(1) x PosEM(DA)	250	0.064	0.245	0	1
MBE(2) x PosEM(DA)	250	0.092	0.290	0	1
MBE(3) x PosEM(DA)	250	0.096	0.295	0	1
MBE(1) x NegEM(DA)	250	0.044	0.206	0	1
MBE(2) x NegEM(DA)	250	0.068	0.252	0	1
MBE(3) x NegEM(DA)	250	0.088	0.284	0	1
MBE(1) x PosEM(Comb)	250	0.124	0.435	0	2
MBE(2) x PosEM(Comb)	250	0.184	0.505	0	2
MBE(3) x PosEM(Comb)	250	0.204	0.517	0	2
MBE(1) x NegEM(Comb)	250	0.088	0.359	0	2
MBE(2) x NegEM(Comb)	250	0.132	0.414	0	2
MBE(3) x NegEM(Comb)	250	0.160	0.446	0	2

MBE() equals 1 if change in EPS compared to last year has been from 0 to 1, 2 or 3 euro cents, and equals 0 otherwise. *PosEM(DA)* and *PosEM(RAM)* equal to 1 if *DA* (calculated using the modified Jones model) or *RAM* (calculated by dividing the negative sum of changes in R&D and advertising expenses by opening total assets) is larger than zero, and equals 0 otherwise, whereas *NegEM(DA)* and *NegEM(RAM)* equal to 1 if *DA* or *RAM* are negative. *PosEM(Comb)* and *NegEM(Comb)* are the sums of both types of earnings management variables. The interaction terms between *MBE()* and *PosEM()* proxy for upwards earnings management, and the interaction terms between *MBE()* and *NegEM()* control for firm-years in which firms have exceeded EPS by 0 to 1, 2 or 3 cents, but have no suspected upwards earnings management based on discretionary accruals or real earnings management.

See Appendix E for a correlation matrix between the variables. Even though there are some strong correlations between the variables, they practically do not enter the same regression models (e.g., *Fog* and *Flesch* have a very strong significant negative correlation, but they are alternative readability proxies), therefore they should not pose a multicollinearity problem in our analysis.

In contrary to what was expected initially, *Age* correlates negatively with length (meaning that older companies tend to write more concisely), however, readability, as measured by *Fog,* tends to be lower for older firms (meaning that with time company managers tend to write more difficult texts), which might stem from the undeveloped stage of the market in which companies are still learning how to report. Also, we would have expected the number of pages in a report (*ln(pages)*) and number of words in MD&A part (*ln(MDAwords)*) to have a quite strong positive correlation with *Fog* and negative with *Flesch* if they could be considered alternative proxies for report readability. However, contrary to what was expected initially and contrary to what has been observed in the United States studies where length is significantly positively correlated with Fog index (e.g., in Li, 2008), one can see that there is virtually no correlation (and it is statistically insignificant) between the length and complexity measures for our sample firm-years. Thus, when reporting our estimation model results, we only report their versions with Fog and Flesch indices as dependent variables.

4.2. Results of model estimations

As stated before, we base our analysis framework on the methods developed by Lo et al. (2017) and Li (2008), who perform the estimations of relationship of readability to firm financials in levels using year and industry fixed effects. To check if this is also the most appropriate estimation form in our case, we perform a comparison between four possible model specifications (see Appendix F). The advantage of using the originally planned version with industry and year dummies, and clustering standard errors around firms (see Appendix F, column I) would be that it is more directly comparable to findings by previous researchers. However, this model specification has quite strong autocorrelation in residuals, meaning that although estimated effects will not be biased, they will not be efficient. Considering that we have panel data, we can also use either fixed or random effects model, including year dummies (see Appendix F, columns II-III). The Hausman test cannot reject the null hypothesis that the difference in coefficients is not systematic (chi2=4.81; Prob>chi2=0.9966), therefore we should use random effects to improve efficiency. The advantage would be that these models would capture all time-invariant firm-fixed effects, so there would be less firm-specific omitted variables possible comparing to the model specification in column I. However, the disadvantages are that in our case with limited number of observations, inserting firm-fixed effects into the model takes away many degrees of freedom, and these models have even higher autocorrelation in residuals, so the estimates would also not be efficient. The final option is to use first-differenced model for our analysis (see Appendix F, column IV), which would also capture all time-invariant firm and industry effects, and would provide more efficient estimates than fixed or random effects models in our case since residuals nearly follow random walk. Henceforth, we choose to employ first-differenced model specifications in our further analysis. Since taking first differences is simply an econometric approach to get rid of time-invariant unobserved factors and obtain unbiased estimates for the model in levels, we still interpret estimation results as if they were in levels for simplicity.

Table 4 shows the results from estimating the relationship between readability and earnings management for the full sample, where earnings management is proxied by *MBE()* ("meet or beat earnings" by 0 to 1, 2, or 3 euro cents). There seems to be no significant relationship neither between earnings management and readability, nor between readability and any other firm financials, except for the significant coefficient on *d.RetVol*, which consistently for both indices shows that if the stock return volatility increases, company has worse MD&A readability (i.e., the text is more difficult), which is in line with the theoretically predicted sign.

Table 5 shows the same estimation, only with the refined definition of earnings management, where positive earnings management is now identified by interaction of *MBE()* and positive management of discretionary accruals, real activities, or both combined. However, the results we obtain are the same as in Table 4, no other coefficients are significant, and the ones that are reported as such in Table 4 remain significant, with the same sign and of a very similar economic magnitude. However, we obtain a negative impact on readability (using both indices) for companies who have exceeded last year's earnings by 0 to 1, 2 or 3 cents, but have no suspected upwards real earnings management, which is not in line with the expected sign.

Table 4. Readability relation to earnings management (identified by *MBE()*).

	Independent variable	Predicted sign	Dependent variable: first-differenced Fog index			Dependent variable: first-differenced Flesch index		
			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈		
			[€0.00, €0.01] I	[€0.00, €0.02] II	[€0.00, €0.03] III	[€0.00, €0.01] IV	[€0.00, €0.02] V	[€0.00, €0.03] VI
β_1	*d.MBE*	+/-	0.276	0.192	-0.0254	-1.102	-0.854	-0.190
			(1.191)	(0.904)	(-0.0981)	(-1.387)	(-1.164)	(-0.211)
β_2	*d.NegEarnChange*	+/-	0.172	0.173	0.0978	-0.946	-0.981	-0.761
			(0.746)	(0.695)	(0.382)	(-1.160)	(-1.113)	(-0.834)
	d.Earnings	-/+	0.752	0.710	0.552	-0.948	-0.844	-0.372
			(0.346)	(0.324)	(0.245)	(-0.116)	(-0.103)	(-0.0445)
	d.Loss	+/-	-0.376	-0.379	-0.370	1.376	1.394	1.365
			(-0.784)	(-0.796)	(-0.779)	(0.874)	(0.889)	(0.873)
	d.Size	+/-	0.537	0.533	0.545	-1.322	-1.300	-1.347
			(1.005)	(0.990)	(1.015)	(-0.591)	(-0.578)	(-0.598)
	d.MTB	+/-	-1.198	-1.090	-1.097	4.254	3.817	3.854
			(-1.586)	(-1.399)	(-1.418)	(1.451)	(1.254)	(1.273)
	d.RetVol	+/-	0.214***	0.209***	0.211***	-0.667***	-0.646***	-0.650***
			(3.816)	(3.594)	(3.594)	(-2.914)	(-2.744)	(-2.749)
	d.EarnVol	+/-	-6.855	-6.666	-6.325	25.13	24.51	23.69
			(-1.490)	(-1.450)	(-1.417)	(1.581)	(1.543)	(1.526)
	d.NBSeg	+/-	-0.935	-0.931	-0.896	3.129	3.131	2.993
			(-1.249)	(-1.256)	(-1.198)	(1.205)	(1.214)	(1.149)
	d.NGSeg	+/-	-0.121	-0.105	-0.0299	1.002	0.971	0.721
			(-0.215)	(-0.189)	(-0.0537)	(0.490)	(0.478)	(0.352)
	Year dummies		No	No	No	No	No	No
	Industry dummies		No	No	No	No	No	No
	Observations		192	192	192	192	192	192
	R-Squared		0.061	0.060	0.057	0.056	0.055	0.051
	$\beta_1 - \beta_2$; $F(1, 54)$=		0.19	0.01	0.29	0.03	0.03	0.52

Table shows regression results of estimating MD&A part text readability as a function of earnings management (proxied by *MBE()*) in first differences. *d.MBE* is the first-differenced *MBE()* that captures firm-years in which previous year's earnings per share were just met or beaten by 1, 2, or 3 cents, and these firms are considered as likely to have managed earnings (*MBE*=1, otherwise *MBE*=0). Baseline group is firms for which earnings per share were beaten by more than 1, 2 or 3 cents. *d.NegEarnChange.* is the first-differenced version of *NegEarnChange* that equals 1 if earnings per share were lower than in the previous year, and 0 otherwise. Control variables are also differenced if they are not constant, but otherwise are as listed in Appendix D. We show the theoretically expected signs for the variables. The model is estimated for the full sample, not including year and industry dummies (because of the differenced specification); standard errors clustered around firms. T-statistics are reported in parenthesis; ***, **, and * are for 1%, 5% and 10% significance levels, respectively.

Table 5. Readability relation to earnings management (identified by *MBE()* and discretionary accruals, and real earnings management).

Panel A: Dependent variable – first-differenced Fog index

	Independent variable	Predicted sign	Accruals earnings management PosEM(DA)=1 if DA>0 and 0 otherwise			Real activities earnings management PosEM(RAM)=1 if RAM>0 and 0 otherwise			Combined earnings management PosEM(Comb)=PosEM(DA)+ +PosEM(RAM)		
			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈		
			[€0.00, €0.01] I	[€0.00, €0.02] II	[€0.00, €0.03] III	[€0.00, €0.01] IV	[€0.00, €0.02] V	[€0.00, €0.03] VI	[€0.00, €0.01] VII	[€0.00, €0.02] VIII	[€0.00, €0.03] IX
β_1	*d.PosEM()*	+	0.0209	0.0142	-0.0311	0.0220	0.0558	0.111	0.0210	0.0349	0.0443
			(0.104)	(0.0706)	(-0.147)	(0.126)	(0.314)	(0.624)	(0.131)	(0.219)	(0.278)
β_2	*d.MBE x PosEM()*	+	0.341	0.284	0.206	-0.0460	-0.125	-0.388	0.0606	-0.00669	-0.106
			(1.149)	(1.082)	(0.750)	(-0.192)	(-0.607)	(-1.508)	(0.402)	(-0.0493)	(-0.722)
β_3	*d.MBE x NegEM()*	0	0.129	0.0360	-0.339	0.685*	0.619**	0.570*	0.264	0.242	0.119
			(0.585)	(0.160)	(-1.043)	(1.867)	(2.079)	(1.828)	(1.329)	(1.469)	(0.608)
β_4	*d.NegEarnChange*	+	0.164	0.162	0.0764	0.180	0.176	0.108	0.179	0.181	0.107
			(0.749)	(0.680)	(0.311)	(0.741)	(0.688)	(0.414)	(0.774)	(0.734)	(0.421)
	d.Earnings	-	0.733	0.706	0.643	0.774	0.722	0.585	0.726	0.656	0.492
			(0.368)	(0.350)	(0.313)	(0.341)	(0.315)	(0.248)	(0.343)	(0.306)	(0.223)
	d.Loss	+	-0.353	-0.344	-0.305	-0.361	-0.372	-0.372	-0.388	-0.405	-0.393
			(-0.694)	(-0.680)	(-0.610)	(-0.755)	(-0.782)	(-0.779)	(-0.781)	(-0.819)	(-0.798)
	Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Year dummies		No	No	No	No	No	No	No	No	No
	Industry dummies		No	No	No	No	No	No	No	No	No
	Observations		192	192	192	192	192	192	192	192	192
	R-Squared		0.062	0.061	0.066	0.069	0.071	0.079	0.063	0.062	0.059
	$\beta_2 - \beta_4$; $F(1, 54)$=		0.29	0.19	0.21	0.49	1.29	3.12*	0.18	0.52	0.64
	$\beta_2 - \beta_3$; $F(1, 54)$=		0.37	0.69	2.78	2.88*	5.74**	9.53***	0.61	1.28	0.91

Panel B: Dependent variable – first-differenced Flesch index

	Independent variable	Predicted sign	Accruals earnings management PosEM(DA)=1 if DA>0 and 0 otherwise			Real activities earnings management PosEM(RAM)=1 if RAM>0 and 0 otherwise			Combined earnings management PosEM(Comb)=PosEM(DA)+ +PosEM(RAM)		
			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈		
			[€0.00, €0.01] I	[€0.00, €0.02] II	[€0.00, €0.03] III	[€0.00, €0.01] IV	[€0.00, €0.02] V	[€0.00, €0.03] VI	[€0.00, €0.01] VII	[€0.00, €0.02] VIII	[€0.00, €0.03] IX
β_1	*d.PosEM()*	-	-0.302	-0.289	-0.156	-0.275	-0.415	-0.594	-0.280	-0.346	-0.383
			(-0.399)	(-0.380)	(-0.199)	(-0.468)	(-0.701)	(-1.032)	(-0.502)	(-0.630)	(-0.696)
β_2	*d.MBE x PosEM()*	-	-1.087	-0.948	-0.727	-0.305	0.192	1.042	-0.269	0.0230	0.350
			(-1.097)	(-1.078)	(-0.785)	(-0.301)	(0.234)	(1.121)	(-0.484)	(0.0459)	(0.664)
β_3	*d.MBE x NegEM()*	0	-0.930	-0.592	0.593	-2.116*	-2.184**	-2.085*	-0.932	-0.990*	-0.655
			(-1.065)	(-0.720)	(0.504)	(-1.696)	(-2.192)	(-1.979)	(-1.401)	(-1.764)	(-0.932)
β_4	*d.NegEarnChange*	-	-0.902	-0.929	-0.681	-0.995	-1.010	-0.807	-0.966	-1.001	-0.787
			(-1.149)	(-1.093)	(-0.768)	(-1.159)	(-1.115)	(-0.866)	(-1.171)	(-1.139)	(-0.863)
	d.Earnings	+	-0.467	-0.410	-0.230	-1.230	-1.110	-0.687	-0.738	-0.498	0.0233
			(-0.0602)	(-0.0526)	(-0.0291)	(-0.146)	(-0.130)	(-0.0791)	(-0.0916)	(-0.0613)	(0.00281)
	d.Loss	-	1.313	1.298	1.168	1.351	1.381	1.380	1.391	1.475	1.446
			(0.791)	(0.788)	(0.718)	(0.854)	(0.877)	(0.874)	(0.853)	(0.907)	(0.894)
	Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Year dummies		No	No	No	No	No	No	No	No	No
	Industry dummies		No	No	No	No	No	No	No	No	No
	Observations		192	192	192	192	192	192	192	192	192
	R-Squared		0.058	0.057	0.057	0.061	0.065	0.071	0.059	0.060	0.056
	$\beta_2 - \beta_4$; $F(1, 54)$=		0.03	0.00	0.00	0.31	1.61	3.74*	0.50	1.24	1.47
	$\beta_2 - \beta_3$; $F(1, 54)$=		0.02	0.12	1.35	1.25	4.45**	9.11***	0.51	1.65	1.36

Table shows regression results of estimating MD&A part text readability as a function of earnings management (proxied by *MBE()* and sign of discretionary accruals or real activity earnings management proxies) in first differences. *d.MBE x PosEM()* is the first-differenced version of *MBE x PosEM()* which estimates the incremental Fog value for firms that met or beat earnings per share by 1, 2 or 3 cents and have positive earnings management signs (a group of firms that are the most likely to have been managing earnings). *d.MBE x NegEM()* is the first-differenced version of *MBE x NegEM()* which estimates incremental Fog value for firms that met or beat earnings per share by 1, 2 or 3 cents, but have no signs of upwards earnings management. Baseline group is firms for which earnings per share were beaten by more than 1, 2 or 3 cents. *d.NegEarnChange* is the first-differenced version of *NegEarnChange* that equals 1 if earnings per share were lower than in the previous year, and 0 otherwise. Control variables are as listed in Appendix D. With "Controls" we mean all variables starting with *d.Size* and ending with *d.NGSeg* that were reported in Table 4; they are not reported for brevity since we obtain the same results as before in terms of sign, magnitude and significance levels for these variables. We show the theoretically expected signs for the variables. The model is estimated for the full sample, not including year and industry dummies (because of the differenced specification); standard errors clustered around firms. T-statistics are reported in parenthesis; ***, **, and * are for 1%, 5% and 10% significance levels, respectively.

We also perform the planned estimation of our models for the more liquid companies using Razums and Vitols' (2017) dataset and our simplified liquidity proxy. The results, which are reported in Table 6, show that when earnings management is proxied by only *MBE()*, we obtain a significant effect with the predicted sign when *MBE()* captures the companies who have exceeded last year's earnings by 0 to 1 euro cents (columns I and IV; however in columns II, III, V and VI the coefficients are also close to being significant). This coefficient (β_1) shows that the difference in reporting complexity is significant between companies who are likely to have been managing earnings and the baseline group (companies who have exceeded last year's EPS by more than three cents). Additionally, the F-statistics reported in Table 6 show that complexity of reporting differs significantly also between companies who have lower EPS than in the prior year (indicated by *NegEarnChange*) and companies who have managed earnings, indicating that for the latter group of firms readability of MD&A text is actually worse than for all other companies (in columns I and IV, but F-statistics in columns II, III, V and VI are close to being significant). Lastly, we see for both indices that in loss years increase in reporting complexity is significant.

With the refined definition of earnings management (Table 7) we see that there is a significant positive effect with both indices and discretionary accruals specification (Panel A and Panel B, columns I-III), meaning that companies who have met or beaten EPS and are suspected to having managed earnings using discretionary accruals, have more complicated MD&A texts. The differences between earnings management companies and the other control groups (i.e., companies with a decrease in EPS, and with a small increase in EPS, but no suspected upwards earnings management) shown by F-statistics are also significant. The same effect also holds for both indices in columns IV and VII when earnings management is proxied by real earnings management and the combination of both.

We observe very similar results when specifying the subsample of liquid firm years as those having stock return volatility (*RetVol*) below the median value in our sample (with the difference that with both Fog and Flesch indices *d.MBE(2)* (as in columns II and V of Table 6) is also significant and with the expected sign, and *d.MBE x PosEM()* for Fog index (as in column VIII of Table 7) is significant. One can see that in the liquid subsample estimations reported in Tables 6 and 7 coefficients are exactly the same when using MBE=1 when change in EPS is from 0 to 2 and from 0 to 3 euro cents, which is due to the fact that among these selected liquid companies there are no firm-years in which increase in EPS would be between 2 and 3 euro cents (hence, *MBE(2)* and *MBE(3)* variables are effectively the same and so are their interactions with earnings management proxies).

Testing for differences between average earnings management proxy values between liquid and illiquid companies in our sample (unreported), we find no statistically significant differences between the earnings management prevalence in these two groups of companies. Therefore, we can conclude that the liquid companies do not manage earnings more or less than illiquid ones in our sample, but they have more incentives for strategic reporting, and hence they also show the significant relationships between earnings management and increased reporting complexity.

In an additional robustness check (see Appendix I) we also verify that the effect on MD&A readability for companies who have managed earnings is truly different between liquid and less liquid firms. We create an interaction term between *MBE()* and a dummy variable *liquid* (that equals to 1 if company is liquid, i.e. if it is included in Razums and Vitols' (2017) sample, and equals 0 otherwise), and in addition to *MBE()* insert variable *liquid* and the interaction term of these two variables into our model[9]. The estimation results are as expected from the previously obtained results for liquid company subsample – one can see that for the liquid companies who have exceeded last year's earnings by 0 to 1, 2, or 3 cents (i.e. have likely managed earnings) the relationship between earnings management and text complexity is positive, but in less liquid companies the same relationship is negative. What it demonstrates is that the link between readability and earnings management for the liquid and less liquid companies is indeed different (as also evidenced by the fact that F-statistic shows that the difference between earnings management variable coefficients β_1 and β_2 in Appendix I is significant).

[9] This time we specify the model in levels to enable including variable *liquid* in the model that would have to be excluded if the estimation were to be performed in first differences.

Table 6: First-differenced estimation results of MD&A complexity as a function of earnings management (identified by *MBE()*) for the subsample of liquid companies.

	Independent variable	Predicted sign (Fog/Flesch)	Dependent variable: first-differenced Fog index			Dependent variable: first-differenced Flesch index		
			MBE=1 when ΔEPS$\in$			MBE=1 when ΔEPS$\in$		
			[€0.00, €0.01] I	[€0.00, €0.02] II	[€0.00, €0.03] III	[€0.00, €0.01] IV	[€0.00, €0.02] V	[€0.00, €0.03] VI
β_1	*d.MBE*	+/-	0.603**	0.355	0.355	-1.828*	-1.181	-1.181
			(2.108)	(1.610)	(1.610)	(-1.934)	(-1.501)	(-1.501)
β_2	*d.NegEarnChange*	+/-	0.0810	0.0757	0.0757	-0.408	-0.430	-0.430
			(0.384)	(0.350)	(0.350)	(-0.497)	(-0.497)	(-0.497)
	d.Earnings	-/+	2.228	2.137	2.137	-4.021	-3.801	-3.801
			(1.559)	(1.520)	(1.520)	(-0.614)	(-0.589)	(-0.589)
	d.Loss	+/-	0.382*	0.400**	0.400**	-1.912***	-1.975***	-1.975***
			(1.954)	(2.043)	(2.043)	(-2.839)	(-3.033)	(-3.033)
	d.Size	+/-	0.202	0.193	0.193	-0.833	-0.773	-0.773
			(0.368)	(0.353)	(0.353)	(-0.362)	(-0.335)	(-0.335)
	d.MTB	+/-	-1.266	-1.061	-1.061	5.101	4.452	4.452
			(-1.670)	(-1.402)	(-1.402)	(1.603)	(1.388)	(1.388)
	d.RetVol	+/-	-0.00541	-0.0221	-0.0221	0.901	0.987	0.987
			(-0.0137)	(-0.0589)	(-0.0589)	(0.631)	(0.707)	(0.707)
	d.EarnVol	+/-	2.069	2.964	2.964	-10.55	-13.12	-13.12
			(0.749)	(1.219)	(1.219)	(-0.877)	(-1.182)	(-1.182)
	d.NBSeg	+/-	0.0595	0.0705	0.0705	-0.367	-0.390	-0.390
			(0.220)	(0.251)	(0.251)	(-0.304)	(-0.317)	(-0.317)
	d.NGSeg	+/-	0.691	0.745	0.745	-0.873	-1.000	-1.000
			(0.785)	(0.848)	(0.848)	(-0.284)	(-0.326)	(-0.326)
	Year dummies		No	No	No	No	No	No
	Industry dummies		No	No	No	No	No	No
	Observations		114	114	114	114	114	114
	R-Squared		0.108	0.091	0.091	0.071	0.064	0.064
	$\beta_1 - \beta_2$; $F(1, 30)$=		4.36**	1.66	1.66	3.26*	1.16	1.16

Table shows regression results of estimating MD&A part text readability as a function of earnings management (proxied by *MBE()*) in first differences for the subsample of liquid companies taken from Razums and Vitols' (2017) thesis dataset. *d.MBE* is first-differenced version of *MBE()* that captures firm-years in which previous year's earnings per share were just met or beaten by 1, 2 or 3 cents, and these firms are considered as likely to have managed earnings (MBE=1, and otherwise MBE=0). Baseline group is firms for which earnings per share were beaten by more than 1, 2 or 3 cents. *d.NegEarnChange* is the first-differenced version of *NegEarnChange* that equals 1 if earnings per share were lower than in the previous year, and 0 otherwise. Control variables are also differenced if they are not constant, but otherwise are as listed in Appendix D. We show the theoretically expected signs for the variables. The model is estimated for the most liquid companies, not including year and industry dummies (because of the differenced specification); standard errors clustered around firms. T-statistics are reported in parenthesis; ***, **, and * are for 1%, 5% and 10% significance levels, respectively.

Table 7. Readability relation to earnings management (identified by *MBE()* and discretionary accruals, and real earnings management), estimated for the subsample of liquid companies.

Panel A: Dependent variable – first-differenced Fog index

	Independent variable	Predicted sign	Accruals earnings management PosEM(DA)=1 if DA>0 and 0 otherwise			Real activities earnings management PosEM(RAM)=1 if RAM>0 and 0 otherwise			Combined earnings management PosEM(Comb)=PosEM(DA)+ +PosEM(RAM)		
			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈		
			[€0.00, €0.01] I	[€0.00, €0.02] II	[€0.00, €0.03] III	[€0.00, €0.01] IV	[€0.00, €0.02] V	[€0.00, €0.03] VI	[€0.00, €0.01] VII	[€0.00, €0.02] VIII	[€0.00, €0.03] IX
β_1	*d.PosEM()*	+	0.0396	0.000120	0.000120	0.101	0.152	0.152	0.0656	0.0722	0.0722
			(0.259)	(0.000782)	(0.000782)	(0.639)	(0.878)	(0.878)	(0.555)	(0.578)	(0.578)
β_2	*d.MBE x PosEM()*	+	0.708**	0.663**	0.663**	0.510***	0.0405	0.0405	0.360**	0.170	0.170
			(2.140)	(2.364)	(2.364)	(3.126)	(0.163)	(0.163)	(2.559)	(1.174)	(1.174)
β_3	*d.MBE x NegEM()*	0	0.193	-0.116	-0.116	0.668	0.713**	0.713**	0.198	0.157	0.157
			(0.672)	(-0.469)	(-0.469)	(1.587)	(2.253)	(2.253)	(0.894)	(1.029)	(1.029)
β_4	*d.NegEarnChange*	+	0.0659	0.0610	0.0610	0.0913	0.0937	0.0937	0.0731	0.0668	0.0668
			(0.307)	(0.278)	(0.278)	(0.417)	(0.432)	(0.432)	(0.344)	(0.311)	(0.311)
	d.Earnings	-	2.121	2.087	2.087	2.316	2.290	2.290	2.144	2.066	2.066
			(1.479)	(1.491)	(1.491)	(1.583)	(1.586)	(1.586)	(1.481)	(1.449)	(1.449)
	d.Loss	+	0.416**	0.516***	0.516***	0.373*	0.377*	0.377*	0.376*	0.393*	0.393*
			(2.118)	(2.761)	(2.761)	(1.796)	(1.789)	(1.789)	(1.824)	(1.818)	(1.818)
	Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Year dummies		No	No	No	No	No	No	No	No	No
	Industry dummies		No	No	No	No	No	No	No	No	No
	Observations		114	114	114	114	114	114	114	114	114
	R-Squared		0.118	0.128	0.128	0.113	0.120	0.120	0.115	0.096	0.096
	$\beta_2 - \beta_4$; *F(1, 30)=*		4.92**	7.16**	7.16**	4.72**	0.03	0.03	1.98	0.25	0.25
	$\beta_2 - \beta_3$; *F(1, 30)=*		2.40	6.02**	6.02**	0.16	3.58*	3.58*	0.62	0.01	0.01

Panel B: Dependent variable – first-differenced Flesch index

	Independent variable	Predicted sign	Accruals earnings management PosEM(DA)=1 if DA>0 and 0 otherwise			Real activities earnings management PosEM(RAM)=1 if RAM>0 and 0 otherwise			Combined earnings management PosEM(Comb)=PosEM(DA)+ +PosEM(RAM)		
			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈		
			[€0.00, €0.01] I	[€0.00, €0.02] II	[€0.00, €0.03] III	[€0.00, €0.01] IV	[€0.00, €0.02] V	[€0.00, €0.03] VI	[€0.00, €0.01] VII	[€0.00, €0.02] VIII	[€0.00, €0.03] IX
β_1	*d.PosEM()*	-	-0.204	-0.0987	-0.0987	-0.312	-0.479	-0.479	-0.241	-0.272	-0.272
			(-0.299)	(-0.141)	(-0.141)	(-0.534)	(-0.769)	(-0.769)	(-0.542)	(-0.588)	(-0.588)
β_2	*d.MBE x PosEM()*	-	-2.010*	-1.940*	-1.940*	-2.229***	-0.359	-0.359	-1.195**	-0.553	-0.553
			(-1.769)	(-1.887)	(-1.887)	(-3.573)	(-0.409)	(-0.409)	(-2.462)	(-1.033)	(-1.033)
β_3	*d.MBE x NegEM()*	0	-0.919	0.0204	0.0204	-1.596	-2.075*	-2.075*	-0.444	-0.526	-0.526
			(-0.763)	(0.0245)	(0.0245)	(-1.149)	(-1.958)	(-1.958)	(-0.585)	(-1.027)	(-1.027)
β_4	*d.NegEarnChange*	-	-0.359	-0.381	-0.381	-0.430	-0.476	-0.476	-0.375	-0.397	-0.397
			(-0.425)	(-0.432)	(-0.432)	(-0.500)	(-0.547)	(-0.547)	(-0.450)	(-0.461)	(-0.461)
	d.Earnings	+	-3.594	-3.517	-3.517	-4.214	-4.250	-4.250	-3.690	-3.537	-3.537
			(-0.539)	(-0.538)	(-0.538)	(-0.633)	(-0.649)	(-0.649)	(-0.557)	(-0.540)	(-0.540)
	d.Loss	-	-1.992***	-2.272***	-2.272***	-1.827**	-1.900**	-1.900**	-1.893**	-1.944**	-1.944**
			(-2.845)	(-3.434)	(-3.434)	(-2.483)	(-2.612)	(-2.612)	(-2.635)	(-2.616)	(-2.616)
	Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Year dummies		No	No	No	No	No	No	No	No	No
	Industry dummies		No	No	No	No	No	No	No	No	No
	Observations		114	114	114	114	114	114	114	114	114
	R-Squared		0.076	0.081	0.081	0.076	0.077	0.077	0.079	0.069	0.069
	$\beta_2 - \beta_4$; *F(1, 30)=*		2.96*	3.80*	3.80*	8.49***	0.02	0.02	1.22	0.04	0.04
	$\beta_2 - \beta_3$; *F(1, 30)=*		0.70	3.22*	3.22*	0.24	2.32	2.32	0.93	0.00	0.00

Table shows regression results of estimating MDA part text readability as a function of earnings management (proxied by *MBE()* and sign of discretionary accruals or real activity earnings management proxies) in first differences for the subsample of liquid companies taken from Razums and Vitols' (2017) thesis dataset. *d.MBE x PosEM()* is the first-differenced *MBE x PosEM()* which estimates the incremental Fog value for firms that met or beat earnings per share by 1, 2, or 3 cents and have positive earnings management signs (a group of firms that are the most likely to have been managing earnings). *d.MBE x NegEM()* is the first-differenced *MBE x NegEM()* which estimates incremental Fog value for firms that met or beat earnings per share by 1, 2 or 3 cents, but have no signs of upwards earnings management. Baseline group is firms for which earnings per share were beaten by more than 1, 2 or 3 cents. *d.NegEarnChange* is the first-differenced *NegEarnChange* which equals 1 if earnings per share were lower than in the previous year, and 0 otherwise. Control variables are as listed in Appendix D. With "Controls" we mean all variables starting with *d.Size* and ending with *d.NGSeg* that were reported in Table 6; they are not reported for brevity since we obtain the same results as before in terms of sign, magnitude and significance levels for these variables (except for *d.MTB* which becomes significant at 10% level in columns II and III for both Fog and Flesch). We show the theoretically expected signs for the variables. The model is estimated for the most liquid companies, not including year and industry dummies (because of the differenced specification); standard errors clustered around firms. T-statistics are reported in parenthesis; ***, **, and * are for 1%, 5% and 10% significance levels, respectively.

With regard to our second research question, Appendix G shows the results from estimating the relationship between language features and earnings management for the full sample, where earnings management is proxied by *MBE()* ("meet or beat earnings" by 0 to 1, 2, or 3 euro cents). Similarly as with readability, there seems to be no significant relationship between earnings management and reporting content (language features) in the full sample. However, we notice that Baltic companies tend to use relatively less self-referential words, relatively more negative words and less causation words in years with loss than during years with profit (see Appendix G, columns I-III, IV-VI and X-XII), less self-referential words when earnings increase, and more self-referential words when stock return volatility increases (Appendix G, columns I-III).

When performing a similar additional test as for our first research question with the subset of most liquid companies in our sample (identified as the ones that are used by Razums and Vitols (2017) in their paper, or by selecting the firm-years with stock return volatility below the median value in our sample, which gives similar results), we see that there still seems to be almost no relationship between earnings management and linguistic features (see Appendix H). We can see that companies that could have managed earnings are more inclined to use less causation words (see Appendix H, column X), although this effect is not very robust across model specifications and in columns XI and XII it is far from being significant. Similarly as in the full sample estimations, companies tend to use less self-referential words when they have loss years and when operating earnings increase (see Appendix H, columns I-III). Some differences appear in magnitudes and/or significance of coefficients, e.g., the decrease in the relative usage frequency of self-referential words in loss years is more significant for liquid companies and more than two times larger in terms of magnitude.

Similarly as for report readability, we also estimate the model with the refined definition of earnings management, where positive earnings management is identified by interaction of *MBE()* and positive management of discretionary accruals, real activities, or both combined. Nevertheless, there appear to be no major differences from the results reported in Appendix G and Appendix H, the same coefficients remain significant as well as no other coefficients become significant, so we do not report these estimations for brevity.

5. Discussion of results

All reported model specifications for the *full sample*, regardless of the readability index and earnings management proxies used, show no significant, robust relationship between earnings management and readability. In the full sample there also seems to be no relationship between readability and any other firm financials or characteristics that we use as control variables, except for stock return volatility. As predicted by theory and found also by Lo et al. (2017) and Li (2008), larger stock volatility increases reporting complexity as firms have more complicated explanations to make. The results from performing estimations on the most *liquid companies* in our sample seem to reveal that there is a positive relation between earnings management and reporting complexity at least for part of the Baltic market.

Also, interestingly the companies both in the full and liquid subsample which have slightly larger EPS than in the previous year, but have no suspected real earnings management, show worse readability than the companies whose EPS is larger by more than three cents comparing to previous year (baseline) and companies who have suspected upwards earnings management, although we expected to have zero incremental effect on readability in that case. This might be so if firms investing more in R&D and/or advertising somehow naturally explain their higher earnings in more complex terms, e.g., because they describe complex research or advertising terms or projects. However, we can also note that Lo et al. (2017) obtained the same significant negative effect on readability for this group of companies when *RAM* was used to proxy for earnings management (the authors did not provide possible explanations for this effect).

What this all seems to imply is that *overall in the market* the reporting that managers do is not strategic, and that it might be rather standardized in this market with companies simply following the established reporting template in their company every year and not varying much in terms of the information they disclose to investors[10]. The fact that the more liquid companies in the sample exhibit a positive relationship between earnings management and reporting complexity (and, as shown in Appendix I estimations, the effect is significantly different from illiquid companies) indicates that perhaps whether management obfuscation hypothesis holds in the market is not that much dependent on overall development stage of the market or

[10] We also attempt to see if that might be the case and observe that pairwise correlations between readability indices and their first lagged values are around 0.7 and significant at 1% level.

accounting/reporting standards used in the country, but rather on how liquid company shares are. If a company's shares are sufficiently liquid, managers have more incentives to strategically report on their performance because they have higher investor following, and, if investors were to discover earnings management and wanted to sell their shares, they could do so more easily, hence increasing the riskiness of earnings management for company managers and strengthening their incentives to report strategically to hide it.

With regard to our second research question, we see that there also is no relation between the linguistic features of the MD&A text (i.e. content of the report) and earnings management when considering the *full sample*, and also no relation can be observed when looking at the *liquid subsample* (we do not consider the effect obtained on causation words to be significant and robust enough to make strong inferences from that). Therefore, even the liquid companies who show a positive relationship between earnings management and overall reporting complexity, show no language features that could be robustly related to earnings management and thus could be considered as being used to increase overall complexity to obfuscate the discrepancy between reported performance and business reality. This effect might be such due to several reasons. Firstly, the liquid companies could be changing other language features (that we did not examine) to increase the overall complexity of the text when strategically reporting on earnings management. Secondly, it might be that Baltic managers do not systematically use specific language features to hide something from annual report readers. Also, having no information on who prepared each MD&A text, there might be a possibility that having several people who do not have similar writing styles compiling the MD&A text does not allow to us to spot linguistic feature relationship with earnings management. Additionally, a reason for lacking a significant relationship might be that we use the English language versions of MD&A report texts, and, while the overall complexity could be argued to remain similar in translation, the specific language features might change. Lastly, it might be the case that the psychology of using different writing styles is different in the context of reporting strategically on earnings management than it is when reporting on financial performance indicators (as examined, e.g., by Li, 2008). That could be so due to more serious obfuscation efforts required in the former case because the negative effect on a company's stock price would be more severe if earnings management were to be discovered by investors than if they were dissatisfied with some financial performance indicators.

Based on our examination of the Baltic states' market, we can conclude that whether managers engage in strategic reporting and the management obfuscation hypothesis holds might be more dependent on a company's liquidity than on overall market development stage/reporting culture/accounting standards. What this implies for this research direction is that the positive relationship between reporting complexity and earnings management might be different depending on how liquid the stock is or on how strong the analyst following is due to varying levels of managers' incentives for strategic reporting.

Also, we can point out that it does not seem that in the Baltic states market report readability or language features could be reliably used by regulators or investors as an additional proxy for spotting earnings management. It would be safer to mainly rely on financial proxies (considering that the relationship did not hold not for all companies and not across all model specifications) unless the company under examination clearly is a liquid one. However, we can also say that on average Baltic company reports in English can be classified as difficult to read, which could be partially hindering liquidity in the market, and an effort could be invested in simplifying the reporting style on the part of regulators and companies themselves.

One limitation for the results and conclusions we draw from them is the relatively small sample size. Because of that we are cautious with extrapolating our conclusions to the entire region with less developed markets. However, we do believe that the hypothesis about the impact of liquidity on whether management obfuscation hypothesis holds in the market or about how large/strong the effect on complexity might be depending on a company's liquidity could serve as a basis for further examination.

As Li (2008) has pointed out, a possible issue arises when analysing language features in annual reports - since research in psychology and linguistics is usually based on language samples that are not part of business communication and are written by people separately (whereas annual report texts are often written by a group of people), external validity of these language content measures is not completely certain. Hence, the tests that are made essentially test together the assumptions on how writing changes if managers are attempting to hide something and the assumption that these language features actually reflect managerial conduct.

Also, a potential limitation arises from the fact that we use English language versions of the MD&A section text instead of the local language versions in Estonian, Latvian and

Lithuanian. Previous research shows mixed evidence on the differences in complexity of translated text (e.g., see Courtis & Hassan, 2002; Dye, 1971), finding that there potentially might be some differences in difficulty levels of a translated text, however, the direction of the effect might be dependent on the specific languages at hand. While analysing the original language versions and/or comparing if there are differences in text complexity levels might be the preferred course of action when encountering uncertainty of this kind, there are a couple of reasons why it cannot be done in our case. The Perl language package and LIWC software, as well as readability formulas, were designed to be used only on English language texts (to our knowledge, there are no equivalent formulas for the Baltic states' languages, and developing them falls outside the scope of this paper). However, based on selectively read text samples in Latvian (our native language) and their versions in English that demonstrate a very close translation in terms of sentence structure and level of difficulty, we rely on an assumption that on average in the sample the differences in readability (if there are any) should not be so large as to bias our results to a significant degree. Moreover, not all of a particular company's investors in the Baltics come from the same country as the company and read annual reports in their original language, therefore, even if there is some translation bias, we believe our results are still relevant with regard to the English translations, and hence relevant to at least part of all investors who buy shares in Baltic companies.

6. Conclusions

In this paper we answer how company MD&A text complexity and content (specific language features) relate to earnings management in the Baltic states. Overall, we find no significant relationship between reporting complexity and earnings management for the full sample of companies in the market, but we do find such a relationship for the liquid company subsample. This possibly indicates that management obfuscation hypothesis could hold not so much depending on the overall market development stage/accounting standards/reporting culture, but rather on a specific company's liquidity level due to the strategic reporting incentives provided by more rigorous monitoring from the outside, which worsens possible impact on stock price if investors were to discover earnings management.

We do not find any significant and robust relationship between language features and earnings management neither in the full sample nor in the liquid company subsample. Not having precise information on the exact annual report preparation process within companies, we hypothesise that the lack of such relationship might be due to managers using other language features (that we do not examine) to increase complexity, or that usage of specific language features to increase complexity is not systematic, or that perhaps the psychological reasons for using these language features differ between cases when obfuscating earnings management and when covering up bad financial performance (which has been examined in previous literature).

Looking ahead, researchers could try to examine factors that determine report readability in the whole Baltic market (besides return volatility), preferably developing readability formulas and/or software that would be compatible with the original language versions of report text to eliminate translation bias considerations. With regard to developed capital markets, we could suggest to split companies in groups based on liquidity and/or degree of analyst coverage and examine whether they also exhibit some differences in the relationship between firm financials/earnings management and report readability and language features, or if liquidity levels only impact this relationship in less developed capital markets, such as the Baltic states market. Additionally, what is still left unanswered by our paper is if there are any language features that do have a relationship with earnings management or this absence of a significant and robust relation was due to some specific features of the Baltic market, therefore, the relationship between content of the annual report texts and earnings management could be still examined further.

7. References

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8. Appendices

Appendix A. Overview of studies on report readability and earnings management in the Baltic states

Author(s) and year of publishing	Title	Market(s)	Data period	Main focus and findings	Notes
Bistrova & Lace (2012)	Quality of Corporate Governance System and Quality of Reported Earnings: Evidence from CEE Companies.	CEE (Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Romania, Poland, Slovakia, Slovenia)	2007-2010	Examines the link between earnings quality and corporate governance quality in CEE companies, and finds that there is a statistically significant negative relationship between cash flow accruals level and corporate governance quality. Also finds that lower earnings quality is associated with discrepancies between operating cash flows and net income in cases when companies have weak corporate governance.	Sample of 118 companies. To detect earnings management use level of accruals (both cash flow and balance sheet) and comparison of net income level to operating cash flow.
Grigorjeva & Lace (2008)	Evaluation of impact of financial result plausibility of Baltic State companies on equity performance.	Baltic States	2002-2007	Examine if and how earnings quality impacts stock performance of listed companies in the Baltic States. Find that performance of companies whose net income exceeds operating cash flow and of those whose operating cash flow exceeds net income is similar over the sample period, and only starting from 2006 share prices for companies whose net income exceeds operating cash flow is lower. Also, find that overall accruals level in Baltic States companies is rather low, with Estonian companies having the lowest accrual levels and Lithuanian companies the highest ones. However, the authors don't find an impact from accruals on share price performance. Overall, claim that earnings quality in Baltic companies is not always high and that Baltic investors do not perform analysis of companies' financial result plausibility, which is why it is not reflected in stock performance.	A sample of 36 publicly listed companies. Measure earnings quality (plausibility) using net income and operating cash flow comparison, and accruals level. Keep companies that were delisted from Baltic Main List during this period in the sample (but don't include banks in the sample).
Garsva, Skuodas, & Rudzioniene (2012)	Earnings Management in European Banks: The Financial Crisis and Increased Incentives for Manipulation through Loan Loss Provisions.	EU-27 countries	2005-2010	Overall, examine earnings management in European banks using loan loss provisions. Confirm that loan loss provisions were used for income smoothing and regulatory capital management, although in the Baltic region, support for the hypothesis is only significant at 20% level (the authors claim that this hypothesis is partly approved for the Baltic states).	Sample of 469 commercial banks, out of which 13 are from Latvia, 7 from Lithuania and 3 from Estonia, and in total they constitute only 4.8% of all observations.
Roo (2011)	Disclosure Discourse: A Shift in Estonian Public Companies' Interim Report Commentaries during the Turn towards Recession	Estonia	2007-2008	Examines how Estonian public companies' interim (quarterly) report commentaries change in terms of sentence complexity and bridges, keywords, references and quotes used, and the perceived nature of the external business environment. The author suggests that increased complexity observed in reporting is due to changes in macroeconomic conditions, and not only because of the relation between increased complexity and worse company performance which has been established in the previous literature.	Qualitative research approach used. Sample consists of companies (13) listed on Tallinn Stock Exchange main list at that moment.

Table 1A. Overview of relevant studies on the Baltic market.

Appendix B. Sample companies and number of firm-years included in the analysis

List	Ticker	Company name	Market	No. of firm-years	List	Ticker	Company name	Market	No. of firm-years
Secondary	AGP1L	Įmonių grupė ALITA	VLN	1	Main	NCN1T	Nordecon	TLN	5
Secondary	ANK1L	Anykščių vynas	VLN	2	Secondary	NKA1R	Nordeka	RIG	3
Main	APG1L	Apranga	VLN	5	Main	OEG1T	Olympic Entertainment Group	TLN	5
Main	ARC1T	Arco Vara	TLN	5	Main	OLF1R	Olainfarm	RIG	4
Secondary	AUG1L	AUGA group	VLN	5	Secondary	PKG1T	Pro Kapital Grupp	TLN	3
Secondary	BAL1R	Latvijas balzams	RIG	5	Main	PRF1T	PRFoods	TLN	5
Main	BLT1T	Baltika	TLN	5	Main	PTR1L	Panevėžio statybos trestas	VLN	5
Main	CTS1L	City Service	VLN	3	Main	PZV1L	Pieno žvaigždės	VLN	5
Main	EEG1T	Ekspress Grupp	TLN	5	Secondary	RER1R	Rīgas elektromašīnbūves rūpnīca	RIG	3
Secondary	FRM1R	Rīgas farmaceitiskā fabrika	RIG	3	Secondary	RJR1R	Rīgas juvelierizstrādājumu rūpnīca	RIG	5
Main	GRD1R	Grindeks	RIG	5	Secondary	RKB1R	Rīgas kuģu būvētava	RIG	5
Main	GRG1L	Grigeo	VLN	5	Secondary	RRR1R	VEF Radiotehnika RRR	RIG	5
Secondary	GRZ1R	Grobiņa	RIG	5	Main	RSU1L	Rokiškio sūris	VLN	5
Secondary	GUB1L	Gubernija	VLN	1	Main	SAF1R	SAF Tehnika	RIG	5
Secondary	GZE1R	Latvijas Gāze	RIG	2	Secondary	SCM1R	Siguldas ciltslietu un mākslīgās apsēklošanas stacija	RIG	5
Main	HAE1T	Harju Elekter	TLN	2	Main	SFGAT	Silvano Fashion Group	TLN	5
Secondary	KA11R	Kurzemes atslēga 1	RIG	5	Main	SKN1T	Skano Group AS	TLN	5
Secondary	KBL1L	Klaipėdos baldai	VLN	2	Secondary	SMA1R	PATA Saldus	RIG	5
Secondary	KCM1R	Kurzemes ciltslietu un mākslīgās apsēklošanas stacija	RIG	5	Secondary	SNG1L	Snaigė	VLN	5
Main	KNF1L	Klaipėdos nafta	VLN	5	Main	TAL1T	Tallink Grupp	TLN	5
Secondary	KNR1L	Kauno energija	VLN	5	Main	TEL1L	Telia Lietuva	VLN	5
Secondary	LAP1R	Liepājas autobusu parks	RIG	2	Secondary	TKB1R	Tosmares kuģubūvētava	RIG	5
Secondary	LJM1R	Latvijas Jūras medicīnas centrs	RIG	5	Main	TKM1T	Tallinna Kaubamaja Grupp	TLN	5
Secondary	LME1R	Liepājas metalurgs	RIG	1	Main	TVEAT	Tallinna Vesi	TLN	5
Main	LNA1L	Linas Agro Group	VLN	4	Main	UTR1L	Utenos trikotažas	VLN	5
Secondary	LNS1L	Linas	VLN	5	Secondary	VDG1L	Vilniaus degtinė	VLN	5
Secondary	LOK1R	Daugavpils Lokomotīvju Remonta Rūpnīca	RIG	5	Main	VLP1L	Vilkyškių pieninė	VLN	5
Secondary	LTT1R	Latvijas tilti	RIG	4	Secondary	VSS1R	Valmieras stikla šķiedra	RIG	5
Main	MRK1T	Merko Ehitus	TLN	5	Secondary	ZMP1L	Žemaitijos pienas	VLN	5

Table 1B. List of sample companies used in estimations.

Appendix C. Description of difficulty levels of Fog and Flesch readability indices

Fog index complexity categories		**Flesch index complexity categories**	
Index value	Complexity category	Index value	Complexity category
≥ 18	"unreadable"	0-30	"very difficult"
14-18	"difficult"	30-50	"difficult"
12-14	"ideal"	50-60	"fairly difficult"
10-12	"acceptable"	60-70	"standard"
8-10	"childish"	70-80	"fairly easy"
		80-90	"easy"
		90-100	"very easy"

Table 1C. Complexity grades of Fog index and Flesch index.
Created by the authors, using information from Li (2008) for Fog index and Courtis (2004) for Flesch index.

Appendix D. Variable definitions

Operating accruals

For calculating total operating accruals we use the following formula (Fairfield, Whisenant, & Yohn, 2003; Gill, Gore, & Rees, 1996):

$$TotAccr_t = \Delta Rec_t + \Delta Inv_t + \Delta OCA_t - \Delta AP_t - \Delta OCL_t - Dep_t \quad (10)$$

where ΔRec_t is change in net receivables from *t-1* to *t*, ΔInv_t is change in inventories from *t-1* to *t*, ΔOCA_t is change in other current assets excluding cash from *t-1* to *t*, ΔAP_t is change in accounts payable from *t-1* to *t*, ΔOCL_t is change in other current liabilities excluding taxes and current portion of long-term debt from *t-1* to *t*, and Dep_t is depreciation and amortization expense in year *t*.

Control variables

Since we also examine earnings management relation to report readability, we use two controlling factors (*Earnings* and *Loss*) like Lo et al. (2017). Besides these two controls added by Lo et al. (2017), we also use most[11] of the non-strategic readability determinants listed by Li (2008). Data was retrieved from Thomson Reuters Eikon unless indicated otherwise.

Variable name	Other authors who have used it	Description
Earnings	Lo et al. (2017)	A variable that measures the ratio of operating earnings divided by opening total assets. This ratio should be negatively related to Fog Index and positively related to Flesch Index, because in years with larger earnings report readability should be better.
Loss	Lo et al. (2017)	A dummy variable that takes a value equal to 1 if *Earnings* is smaller than zero (and a value equal to 0 otherwise). It is used to control for loss-making years since that kind of situation would necessitate description of why the business is viable, which could decrease report readability.
Size	Lo et al. (2017) & Li (2008)	Since larger firms could be expected to have more difficult and longer annual reports, *Size*, which is proxied by logarithm of market value at the end of the fiscal year, is included to control for report readability.
MTB	Lo et al. (2017) & Li (2008)	Growth and value firms differ in many aspects, and in the context of our research it could be expected that growth firms

[11] We do not use a variable to differentiate between companies who have been incorporated in Delaware for obvious reasons and also do not use a variable to control for special items due to unavailability of such data in Thomson Reuters Eikon database. Lo et al. (2017) and Li (2008) also use two distinct types of firm events - mergers and acquisitions and seasoned equity offerings - to proxy for the additional disclosures that might be needed in relation to that. However, both of these event types are rare in the Baltic market, therefore we do not include them in our model as they would not be relevant. Likewise, they use the number of non-missing items in the standardized financial statements to proxy for financial complexity, however, we do not employ this measure since it is not that crucial for the Baltic market and based on our observation that sometimes in Thomson Reuters Eikon some data is missing, this proxy would be very noisy in our case.

		have more complex annual reports since their business is more uncertain and difficult to understand. Therefore, *MTB* (market-to-book) ratio of assets is calculated as (market value of equity+book value of liabilities)/book value of total assets at the fiscal year-end and is included as one of determinants of readability[12].
Age	Lo et al. (2017) & Li (2008)	Since there is more information available (and therefore less uncertainty and information asymmetry) about business operations of older firms, their annual reports might need to explain less complex information, and therefore be more easily readable. *Age* is defined as the number of years since incorporation of the company and is obtained from Nasdaq OMX Baltic website (or, where the information is missing, from Orbis database).
RetVol & *EarnVol*	Lo et al. (2017) & Li (2008)	Volatility of the business environment a firm operates in might also influence report readability - the higher volatility, the more complicated explanations will be necessary in annual reports. We use two proxies for volatility: *RetVol*, the standard deviation of monthly stock returns[13] of a firm in the previous year, and *EarnVol*, the standard deviation of operating earnings (deflated by total assets) during the previous five fiscal years.
NBSeg & *NGSeg*	Lo et al. (2017) & Li (2008)	Since complexity of business operations might also make reporting inherently more complex, we control for that using the number of business segments (*NBSeg*) and number of geographic segments (*NGSeg*) measured as the logarithm of the reported number of these segments in Thomson Reuters Eikon for the respective fiscal year[14].
dEE, *dLT* & *dLV*	Conceptually similar to dummy controlling for incorporation in Delaware as in Lo et al. (2017) & Li (2008)	Since our sample is composed of companies from three countries, which still might have some differences in reporting requirements, reporting culture, style of writing, etc., we control for origin country of the company by using dummies *dEE* (equals 1 if company is from Estonia), *dLT* (equals 1 if company is from Lithuania), and *dLV* (equals 1 if company is from Latvia). We have no initial expectations on the readability differences between countries.
d_p	-	Specific feature of the Baltic stock market is also that companies are listed either on Main List or Secondary List, and they have different trading and reporting requirements depending on that, so we also add a dummy variable *d_p* to control for that (*d_p* equals to 1 if company is in the Main List). We also have no initial expectations on the relationship that this factor could have with report readability.

Table 1D. Control variable descriptions and sources.
Created by the authors using information from Lo et al. (2017) and Li (2008).

[12] If data on market value is not available in Thomson Reuters Datastream, we retrieve the stock price on the last day of the year from NASDAQ OMX Baltic website and multiply it by the number of shares outstanding during that year to obtain the necessary market value for calculating variables *Size* and *MTB* for those firms.

[13] To calculate returns, we use unadjusted prices (UP), i.e. the actual closing prices recorded on that day, from Thomson Reuters Datastream.

[14] If there are years for which segment data is not available, we fill in the missing data by looking at the company's annual report files available on NASDAQ OMX Baltic website.

Appendix E. Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1) *ΔEPS*	1.00																							
(2) *MBE(1)*	0.01	1.00																						
(3) *MBE(2)*	0.01	**0.80**	1.00																					
(4) *MBE(3)*	0.02	**0.73**	**0.92**	1.00																				
(5) *NegEarnChange*	**-0.31**	**-0.34**	**-0.43**	**-0.46**	1.00																			
(6) *Earnings*	**0.25**	**0.12**	**0.15**	**0.12**	**-0.25**	1.00																		
(7) *RAM*	-0.01	-0.01	0.03	0.04	-0.03	-0.05	1.00																	
(8) *DA*	**0.11**	0.08	0.05	0.03	-0.09	**0.16**	**-0.14**	1.00																
(9) *ln(pages)*	0.07	**0.15**	**0.21**	**0.16**	**-0.11**	**0.23**	0.05	**0.18**	1.00															
(10) *ln(MDAwords)*	0.07	**0.16**	**0.19**	**0.16**	**-0.11**	**0.27**	0.04	0.09	**0.90**	1.00														
(11) *Fog*	0.00	0.02	-0.02	-0.04	0.00	-0.09	0.03	0.10	-0.10	-0.07	1.00													
(12) *Flesch*	-0.01	-0.02	0.00	0.00	0.04	0.01	-0.05	**-0.13**	0.00	-0.01	**-0.92**	1.00												
(13) *IvsU*	-0.01	**-0.23**	**-0.19**	**-0.15**	0.03	0.06	-0.08	-0.08	**-0.23**	**-0.11**	**-0.19**	**0.20**	1.00											
(14) *cause*	-0.06	-0.10	-0.08	-0.04	0.03	**-0.23**	0.02	0.03	**-0.24**	**-0.35**	**0.34**	**-0.30**	-0.02	1.00										
(15) *PvsN*	**0.11**	0.07	**0.11**	0.07	**-0.18**	**0.38**	0.08	**0.13**	**0.34**	**0.30**	-0.08	-0.01	-0.07	0.08	1.00									
(16) *FvsP*	0.03	-0.04	-0.01	0.00	-0.07	0.00	-0.04	-0.02	0.06	0.05	**0.11**	**-0.12**	0.07	-0.08	**-0.14**	1.00								
(17) *Loss*	**-0.32**	**-0.13**	**-0.15**	**-0.12**	**0.29**	**-0.58**	-0.01	**-0.23**	**-0.31**	**-0.30**	0.03	0.02	-0.07	**0.12**	**-0.47**	0.00	1.00							
(18) *Size*	0.05	0.08	**0.11**	0.05	-0.06	**0.49**	0.01	**0.13**	**0.64**	**0.68**	**-0.22**	**0.14**	0.02	**-0.34**	**0.46**	-0.02	**-0.41**	1.00						
(19) *Age*	-0.02	**-0.12**	**-0.16**	**-0.15**	0.05	**-0.29**	-0.01	-0.07	**-0.54**	**-0.59**	**0.13**	0.00	**0.11**	0.08	**-0.29**	0.00	**0.31**	**-0.44**	1.00					
(20) *MTB*	-0.01	**0.17**	**0.18**	**0.14**	-0.04	**0.47**	-0.09	-0.08	**0.23**	**0.32**	**-0.19**	**0.16**	0.09	**-0.30**	**0.18**	**0.13**	**-0.19**	**0.54**	**-0.31**	1.00				
(21) *RetVol*	-0.03	-0.02	-0.03	-0.03	0.07	**-0.28**	0.00	**-0.16**	**-0.14**	**-0.11**	0.10	-0.09	0.01	0.06	-0.06	**0.20**	**0.15**	**-0.17**	**0.13**	**0.11**	1.00			
(22) *EarnVol*	-0.06	0.00	-0.03	0.00	0.00	**0.21**	-0.08	-0.07	**-0.18**	-0.06	-0.03	0.04	**0.23**	-0.04	**-0.13**	0.05	-0.04	**-0.11**	**-0.16**	**0.22**	0.00	1.00		
(23) *NBSeg*	-0.03	0.01	-0.05	-0.04	0.02	0.00	-0.04	-0.04	**-0.11**	0.03	0.04	-0.03	0.02	-0.05	-0.03	**-0.18**	0.01	-0.04	**-0.25**	**-0.15**	0.05	0.07	1.00	
(24) *NGSeg*	0.02	-0.03	0.04	0.01	0.02	-0.01	0.02	-0.02	0.03	-0.05	**-0.22**	**0.23**	0.08	-0.04	-0.09	**-0.11**	0.06	0.00	**0.32**	-0.03	-0.10	-0.02	**-0.28**	1.00

Table 1E. Pairwise correlations between the most important variables.
Table displays correlations between the most important variables. Bolded correlation coefficients are significant at a 10% level or better.

Appendix F. Comparison of regression in levels, fixed effects and random effects regression, and first differenced regression

Independent variable for columns I-III	Predicted sign (Fog)	I Originally planned model	II Fixed effects regression	III Random effects regression	IV First-differenced regression	Independent variable for column IV
MBE	+	-0.158	0.124	0.113	0.192	*d.MBE*
		(-0.462)	(0.528)	(0.492)	(0.904)	
NegEarnChange	+	0.175	0.247	0.262	0.173	*d.NegEarnChange*
		(0.697)	(1.045)	(1.163)	(0.695)	
Earnings	-	0.968	0.362	0.796	0.710	*d.Earnings*
		(0.544)	(0.233)	(0.549)	(0.324)	
Loss	+	0.0433	-0.534	-0.473	-0.379	*d.Loss*
		(0.0784)	(-0.996)	(-0.890)	(-0.796)	
Size	+	-0.00969	0.182	0.0160	0.533	*d.Size*
		(-0.0450)	(0.578)	(0.108)	(0.990)	
MTB	+	-0.0435	-0.218	-0.202	-1.090	*d.MTB*
		(-0.0867)	(-0.331)	(-0.459)	(-1.399)	
Age	-	0.00422	0.144**	-0.00481		
		(0.361)	(2.013)	(-0.739)		
RetVol	+	0.0754	0.278***	0.239***	0.209***	*d.RetVol*
		(0.817)	(5.551)	(6.582)	(3.594)	
EarnVol	+	-0.0930	-4.826	-2.129	-6.666	*d.EarnVol*
		(-0.0274)	(-1.186)	(-0.799)	(-1.450)	
NBSeg	+	0.0462	-0.584	-0.263	-0.931	*d.NBSeg*
		(0.100)	(-0.581)	(-0.678)	(-1.256)	
NGSeg	+	-0.237	0.137	-0.155	-0.105	*d.NGSeg*
		(-0.731)	(0.227)	(-0.573)	(-0.189)	
d_p	?	-1.533**	-1.000***	-1.891***		
		(-2.231)	(-3.918)	(-3.304)		
dEE	?	-0.456				
		(-0.486)				
dLT	?	0.935				
		(0.949)				
Constant		17.96***	12.35***	18.91***		
		(9.898)	(5.010)	(13.00)		
Year dummies		Yes	Yes	Yes	No	
Industry dummies		Yes	No	No	No	
Observations		250	250	250	192	
R-Squared		0.298	0.107	0.1925	0.060	

Table 1F. Estimation results of MD&A text readability as a function of earnings management, model comparison. Table shows regression results of estimating MD&A part text readability (proxied by Fog index in columns I-III and by first-differenced Fog index in column IV) as a function of earnings management (proxied by *MBE*=1 when $\Delta EPS \in$[€0.00, €0.02]). Baseline group is firms for which earnings per share were beaten by more than two cents. *NegEarnChange*=1 if earnings per share were lower than in the previous year, and 0 otherwise. Control variables are as listed in Appendix D. We show the theoretically expected signs for the variables, and where there was no specific prediction beforehand, we enter "?". The model is estimated for the full sample. Industry dummies based on Fama-French 12 industry classification. T-statistics are reported in parenthesis; ***, **, and * are for 1%, 5% and 10% significance levels, respectively.

Appendix G. Estimation results of MD&A content (language features) as a function of earnings management

Independent variable	Dependent variable: first-differenced IvsU			Dependent variable: first-differenced PvsN			Dependent variable: first-differenced FvsP			Dependent variable: first-differenced cause		
	MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈			MBE=1 when ΔEPS∈		
	[€0.00, €0.01] I	[€0.00, €0.02] II	[€0.00, €0.03] III	[€0.00, €0.01] IV	[€0.00, €0.02] V	[€0.00, €0.03] VI	[€0.00, €0.01] VII	[€0.00, €0.02] VIII	[€0.00, €0.03] IX	[€0.00, €0.01] X	[€0.00, €0.02] XI	[€0.00, €0.03] XII
β_1 *d.MBE*	-0.00682	0.00329	0.0182	0.0247	0.00167	0.00703	-0.0147	-0.0190	-0.0149	-0.0209	-0.00129	-0.0268
	(-0.118)	(0.0725)	(0.592)	(0.810)	(0.0589)	(0.177)	(-0.509)	(-0.722)	(-0.469)	(-0.213)	(-0.0159)	(-0.306)
β_2 *d.NegEarnChange*	-0.0168	-0.0141	-0.00836	-0.00980	-0.0150	-0.0129	0.00239	-0.000675	0.000231	0.0175	0.0219	0.0123
	(-0.634)	(-0.534)	(-0.345)	(-0.379)	(-0.532)	(-0.467)	(0.101)	(-0.0268)	(0.00862)	(0.270)	(0.337)	(0.179)
d.Earnings	-0.411***	-0.404***	-0.392***	0.456	0.441	0.445	0.0864	0.0823	0.0849	-0.745	-0.732	-0.752
	(-2.683)	(-2.753)	(-2.762)	(1.472)	(1.431)	(1.450)	(0.374)	(0.356)	(0.368)	(-1.144)	(-1.127)	(-1.150)
d.Loss	-0.0569*	-0.0572*	-0.0577*	-0.127***	-0.126***	-0.127***	-0.0290	-0.0284	-0.0287	-0.240*	-0.240*	-0.239*
	(-1.849)	(-1.862)	(-1.905)	(-3.284)	(-3.257)	(-3.252)	(-0.652)	(-0.638)	(-0.643)	(-1.893)	(-1.901)	(-1.893)
d.Size	0.133**	0.133**	0.133**	-0.00928	-0.00870	-0.00879	-0.0116	-0.0109	-0.0116	0.0294	0.0289	0.0296
	(2.345)	(2.332)	(2.349)	(-0.128)	(-0.120)	(-0.121)	(-0.141)	(-0.131)	(-0.140)	(0.183)	(0.179)	(0.184)
d.MTB	-0.228***	-0.231***	-0.231***	-0.102	-0.0933	-0.0935	-0.0450	-0.0512	-0.0502	-0.0384	-0.0460	-0.0457
	(-2.902)	(-3.026)	(-3.063)	(-1.238)	(-1.161)	(-1.157)	(-0.368)	(-0.419)	(-0.412)	(-0.184)	(-0.217)	(-0.216)
d.RetVol	0.0131**	0.0131**	0.0131**	0.0211***	0.0208***	0.0207***	0.000106	0.000430	0.000402	0.0193	0.0196	0.0198
	(2.271)	(2.287)	(2.292)	(2.773)	(2.742)	(2.737)	(0.0141)	(0.0572)	(0.0533)	(0.919)	(0.915)	(0.921)
d.EarnVol	1.086	1.070	1.033	-0.596	-0.557	-0.570	0.0766	0.0795	0.0855	-0.549	-0.583	-0.524
	(1.535)	(1.502)	(1.454)	(-0.723)	(-0.673)	(-0.684)	(0.161)	(0.168)	(0.180)	(-0.504)	(-0.540)	(-0.482)
d.NBSeg	-0.0582	-0.0597	-0.0604	0.0132	0.0163	0.0161	-0.0203	-0.0190	-0.0213	0.0105	0.00792	0.00948
	(-1.150)	(-1.184)	(-1.191)	(0.238)	(0.293)	(0.294)	(-0.310)	(-0.288)	(-0.325)	(0.0877)	(0.0666)	(0.0796)
d.NGSeg	-0.0295	-0.0327	-0.0368	-0.153	-0.146	-0.147	-0.113	-0.111	-0.114*	-0.149	-0.155	-0.147
	(-0.696)	(-0.811)	(-0.966)	(-1.478)	(-1.430)	(-1.385)	(-1.664)	(-1.666)	(-1.697)	(-1.107)	(-1.154)	(-1.107)
Year dummies	No	No	No	No	No	No	No	No	No	No	No	No
Industry dummies	No	No	No	No	No	No	No	No	No	No	No	No
Observations	192	192	192	192	192	192	192	192	192	192	192	192
R-Squared	0.101	0.101	0.103	0.175	0.173	0.173	0.029	0.030	0.029	0.041	0.041	0.041
$\beta_1 - \beta_2$; $F(1, 54)$=	0.05	0.25	1.08	1.92	0.61	0.38	0.38	0.57	0.34	0.22	0.10	0.30

Table 1G. First-differenced estimation results of MD&A text language features as a function of earnings management.
Table shows regression results of estimating MD&A part text readability as a function of earnings management (proxied by *MBE()*) in first differences. *d.MBE* is first-differenced version of *MBE()* that captures firm-years in which previous year's earnings per share were just met or beaten by 1, 2 or 3 cents, and these firms are considered as likely to have managed earnings (MBE=1, and otherwise MBE=0). Baseline group is firms for which earnings per share were beaten by more than 1, 2 or 3 cents. *d.NegEarnChange* is the first-differenced version of *NegEarnChange* that equals 1 if earnings per share were lower than in the previous year, and 0 otherwise. Control variables are also differenced if they are not constant, but otherwise are as listed in Appendix D. The model is estimated for the full sample, not including year and industry dummies (because of the differenced specification); standard errors clustered around firms. T-statistics are reported in parenthesis; ***, **, and * are for 1%, 5% and 10% significance levels, respectively.

Appendix H. Estimation results of MD&A content (language features) as a function of earnings management for the liquid company subsample

Independent variable	Dependent variable: first-differenced IvsU MBE=1 when ΔEPS∈			Dependent variable: first-differenced PvsN MBE=1 when ΔEPS∈			Dependent variable: first-differenced FvsP MBE=1 when ΔEPS∈			Dependent variable: first-differenced cause MBE=1 when ΔEPS∈		
	[€0.00, €0.01] I	[€0.00, €0.02] II	[€0.00, €0.03] III	[€0.00, €0.01] IV	[€0.00, €0.02] V	[€0.00, €0.03] VI	[€0.00, €0.01] VII	[€0.00, €0.02] VIII	[€0.00, €0.03] IX	[€0.00, €0.01] X	[€0.00, €0.02] XI	[€0.00, €0.03] XII
β_1 *d.MBE*	0.0478	0.0436	0.0436	0.0574	0.0280	0.0280	-0.0395	-0.0349	-0.0349	-0.154**	-0.0564	-0.0564
	(0.922)	(1.229)	(1.229)	(1.270)	(0.838)	(0.838)	(-0.808)	(-0.897)	(-0.897)	(-2.130)	(-0.696)	(-0.696)
β_2 *d.NegEarnChange*	0.00671	0.0119	0.0119	0.0242	0.0215	0.0215	-0.000107	-0.00396	-0.00396	-0.0313	-0.0175	-0.0175
	(0.200)	(0.388)	(0.388)	(0.939)	(0.763)	(0.763)	(-0.00492)	(-0.169)	(-0.169)	(-0.410)	(-0.230)	(-0.230)
d.Earnings	-0.483***	-0.482***	-0.482***	0.111	0.0993	0.0993	0.236	0.236	0.236	-0.432	-0.391	-0.391
	(-3.395)	(-3.456)	(-3.456)	(0.491)	(0.442)	(0.442)	(1.304)	(1.225)	(1.225)	(-1.038)	(-0.947)	(-0.947)
d.Loss	-0.139**	-0.137**	-0.137**	-0.0779	-0.0765	-0.0765	-0.0478	-0.0497	-0.0497	-0.264	-0.266	-0.266
	(-2.546)	(-2.508)	(-2.508)	(-1.446)	(-1.385)	(-1.385)	(-0.593)	(-0.616)	(-0.616)	(-1.480)	(-1.509)	(-1.509)
d.Size	0.143	0.138	0.138	0.0483	0.0493	0.0493	-0.0381	-0.0338	-0.0338	0.259	0.250	0.250
	(1.552)	(1.546)	(1.546)	(0.538)	(0.556)	(0.556)	(-0.425)	(-0.382)	(-0.382)	(1.150)	(1.129)	(1.129)
d.MTB	-0.256**	-0.236**	-0.236**	-0.0645	-0.0464	-0.0464	0.103	0.0868	0.0868	0.0388	-0.00513	-0.00513
	(-2.498)	(-2.550)	(-2.550)	(-0.608)	(-0.458)	(-0.458)	(1.242)	(1.078)	(1.078)	(0.118)	(-0.0159)	(-0.0159)
d.RetVol	0.0859	0.0793	0.0793	-0.00757	-0.00719	-0.00719	-0.179	-0.174	-0.174	-0.127	-0.134	-0.134
	(0.939)	(0.921)	(0.921)	(-0.109)	(-0.0991)	(-0.0991)	(-1.011)	(-0.972)	(-0.972)	(-0.667)	(-0.687)	(-0.687)
d.EarnVol	1.294	1.344	1.344	0.537	0.631	0.631	0.522	0.479	0.479	1.936	1.659	1.659
	(1.083)	(1.065)	(1.065)	(0.737)	(0.850)	(0.850)	(0.754)	(0.701)	(0.701)	(1.275)	(1.081)	(1.081)
d.NBSeg	-0.101	-0.101	-0.101	0.0127	0.0143	0.0143	-0.0354	-0.0350	-0.0350	0.0250	0.0188	0.0188
	(-1.539)	(-1.557)	(-1.557)	(0.222)	(0.256)	(0.256)	(-0.598)	(-0.590)	(-0.590)	(0.260)	(0.207)	(0.207)
d.NGSeg	0.0101	0.00915	0.00915	0.00832	0.0154	0.0154	-0.185***	-0.185***	-0.185***	0.137	0.111	0.111
	(0.165)	(0.157)	(0.157)	(0.168)	(0.327)	(0.327)	(-3.966)	(-3.757)	(-3.757)	(0.981)	(0.798)	(0.798)
Year dummies	No	No	No	No	No	No	No	No	No	No	No	No
Industry dummies	No	No	No	No	No	No	No	No	No	No	No	No
Observations	114	114	114	114	114	114	114	114	114	114	114	114
R-Squared	0.161	0.164	0.164	0.091	0.080	0.080	0.104	0.105	0.105	0.087	0.076	0.076
$\beta_1 - \beta_2$; $F(1, 30)$=	1.59	1.18	1.18	0.92	0.09	0.09	0.79	0.90	0.90	3.24*	0.21	0.21

Table 1H. First-differenced estimation results of MD&A text language features as a function of earnings management for the subsample of liquid companies.
Table shows regression results of estimating MD&A part text readability as a function of earnings management (proxied by *MBE()*) in first differences for the subsample of liquid companies taken from Razums and Vitols' (2017) thesis dataset. *d.MBE* is first-differenced version of *MBE()* that captures firm-years in which previous year's earnings per share were just met or beaten by 1, 2 or 3 cents, and these firms are considered as likely to have managed earnings (MBE=1, and otherwise MBE=0). Baseline group is firms for which earnings per share were beaten by more than 1, 2 or 3 cents. *d.NegEarnChange* is the first-differenced version of *NegEarnChange* that equals 1 if earnings per share were lower than in the previous year, and 0 otherwise. Control variables are also differenced if they are not constant, but otherwise are as listed in Appendix D. The model is estimated for the full sample, not including year and industry dummies (because of the differenced specification); standard errors clustered around firms. T-statistics are reported in parenthesis; ***, **, and * are for 1%, 5% and 10% significance levels, respectively.

Appendix I. Estimation results of MD&A text complexity as a function of earnings management, depending on companies' liquidity

	Independent variable	Dependent variable: first-differenced Fog index MBE=1 when ΔEPS∈			Dependent variable: first-differenced Flesch index MBE=1 when ΔEPS∈		
		[€0.00, €0.01] I	[€0.00, €0.02] II	[€0.00, €0.03] III	[€0.00, €0.01] IV	[€0.00, €0.02] V	[€0.00, €0.03] VI
β_1	*MBE*	-0.879*	-0.890*	-1.388**	2.922	2.882	3.870**
		(-1.682)	(-1.718)	(-2.434)	(1.522)	(1.556)	(2.155)
β_2	*MBE x liquid*	1.488*	1.258*	1.670**	-3.078	-3.262	-4.051**
		(2.000)	(1.981)	(2.431)	(-1.239)	(-1.568)	(-2.024)
β_3	*liquid*	0.133	0.131	0.0393	-0.196	-0.0837	0.135
		(0.124)	(0.122)	(0.0371)	(-0.0568)	(-0.0244)	(0.0399)
β_4	*NegEarnChange*	0.195	0.179	0.0444	-0.403	-0.389	-0.0715
		(0.861)	(0.708)	(0.183)	(-0.525)	(-0.468)	(-0.0853)
	Earnings	0.813	0.753	0.498	-4.485	-4.715	-4.091
		(0.516)	(0.473)	(0.319)	(-0.713)	(-0.739)	(-0.648)
	Loss	-0.00332	-0.00654	0.0270	0.384	0.331	0.225
		(-0.00604)	(-0.0119)	(0.0497)	(0.203)	(0.175)	(0.119)
	Size	-0.0624	-0.0668	-0.0765	0.0910	0.102	0.122
		(-0.222)	(-0.241)	(-0.282)	(0.0907)	(0.102)	(0.124)
	MTB	-0.0521	-0.0197	-0.0111	-0.172	-0.0927	-0.101
		(-0.0813)	(-0.0327)	(-0.0186)	(-0.0807)	(-0.0456)	(-0.0503)
	Age	0.00293	0.00273	0.00135	0.0184	0.0197	0.0228
		(0.257)	(0.237)	(0.117)	(0.527)	(0.558)	(0.640)
	RetVol	0.0663	0.0619	0.0579	-0.274	-0.278	-0.268
		(0.659)	(0.630)	(0.584)	(-0.812)	(-0.845)	(-0.813)
	EarnVol	-0.226	-0.465	-0.0640	10.23	10.77	9.549
		(-0.0641)	(-0.133)	(-0.0176)	(0.682)	(0.725)	(0.625)
	NBSeg	0.0444	0.0496	0.0401	0.322	0.367	0.390
		(0.0986)	(0.108)	(0.0878)	(0.219)	(0.246)	(0.262)
	NGSeg	-0.220	-0.213	-0.190	0.123	0.107	0.0639
		(-0.697)	(-0.673)	(-0.610)	(0.121)	(0.106)	(0.0635)
	d_p	-1.735*	-1.793*	-1.930**	5.916**	5.975**	6.297**
		(-1.926)	(-1.994)	(-2.207)	(2.178)	(2.237)	(2.422)
	Constant	18.44***	18.48***	18.77***	29.52***	29.20***	28.52***
		(9.316)	(9.350)	(9.572)	(4.046)	(3.957)	(3.882)
	Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
	Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
	Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
	Observations	250	250	250	250	250	250
	R-Squared	0.308	0.308	0.321	0.296	0.297	0.305
	$\beta_2 - \beta_1$; $F(1, 57)$=	4.18**	4.00*	6.62**	2.14	2.73	4.91**

Table 1I. Readability relation to earnings management (identified by *MBE()*), estimated by separating out the effect for liquid companies.

Table shows regression results of estimating MD&A part text readability as a function of earnings management (proxied by *MBE()*). *MBE* captures firm-years in which previous year's earnings per share were just met or beaten by 1, 2 or 3 cents, and these firms are considered as likely to have managed earnings (*MBE*=1, and otherwise *MBE*=0). *liquid* is a dummy equal to 1 if company is identified as liquid (i.e. it is included in Razums and Vitols' (2017) thesis dataset), and 0 otherwise. *MBE x liquid* is an interaction term between the respective two variables and differentiates liquid companies who are likely to have managed earnings from less liquid companies. *NegEarnChange* equals 1 if earnings per share were lower than in the previous year, and 0 otherwise. Control variables are as listed in Appendix D. The model is estimated for the full sample, including country, year, and industry dummies; standard errors clustered around firms. T-statistics are reported in parenthesis; ***, **, and * are for 1%, 5% and 10% significance levels, respectively.