



Universitetet
i Stavanger

**FACULTY OF SOCIAL SCIENCES,
UIS BUSINESS SCHOOL**

MASTER'S THESIS

<p>STUDY PROGRAM:</p> <p>MSc Business Administration</p>	<p>THESIS IS WRITTEN IN THE FOLLOWING SPECIALIZATION/SUBJECT:</p> <p>Applied finance</p> <p>IS THE ASSIGNMENT CONFIDENTIAL? (NB! Use the red form for confidential theses)</p>
<p>TITLE:</p> <p>Comparative Analysis of Textual-Content in Corporate Financial Disclosures and Implications on Future Stock Return</p>	

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Comparative Analysis of
Textual-Content in Corporate
Financial Disclosures and
Implications on Future Stock
Return

*A STUDY OF THE NORWEGIAN STOCK MARKET AND
ITS PARTICIPANTS*

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Foreword

This master thesis has been written to fulfill the graduation requirements of the two-year Master of Science in Business and Administration program with the specialization in Applied Finance at the University of Stavanger Business School.

Working with the thesis proved to be a challenging but rewarding task. Through the writing process, we have gained much knowledge in several exciting areas and especially within the field of Computational Linguistics and Natural Language Processing.

We would like to offer our gratitude to UiS Business School for granting funding for development of a textual analysis software, Ilgar Isgandarov for supervision and support during our work on the thesis, Bernt Arne Odegaard for sharing his knowledge about the Norwegian stock market, Dengjun Zhang for the inputs on econometric methods and Bill McDonald for explaining the approach in development of Loughran McDonald Master Dictionary. We are grateful for all the helpful people we met along the way.

Abstract

The objective of this thesis is to investigate the extent to which year-over-year changes in textual-content and structure in quarterly and annual financial disclosures across companies listed at Norwegian Stock Exchange may provide valuable information associated with future returns. Specifically, we seek to provide insights into the usefulness of the text-based financial analysis of annual and quarterly reports to companies' outsiders. This paper contributes to an increased understanding of the informational value of the narrative sections of financial disclosures, investigating the usefulness of textual information to investors. We find that substantial changes to the textual content of corporate financial disclosures are associated with lower returns in the following three-month period. We also find that increased use of words related to negative sentiment (tone of language) is also associated with lower returns. Exploring a possible mechanism of what is causing the change in disclosures to indicate lower returns, we find a plausible explanation where negative sentiment in the disclosures is positively associated with the increased change to textual content.

Keywords: Textual analysis, corporate disclosures, similarity, sentiment, information.

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1. Introduction

1.1 Background

Corporate financial disclosures are viewed to be an essential aspect of any business. The fundamental intention of the financial disclosures is to provide a clear picture of the company's development and financial health for a given period, thus revealing the relevant information about performances that may influence investment decision of corporate outsiders. In this context, corporate financial disclosures play the role of valuable input for outside users' perception of companies' fundamental value and quality of their management. For years, the content of financial disclosures mainly oriented on providing "cold" accounting numbers offering little information or insights about other aspects affecting the business. Non-financial information in the form of narratives written by management and extensive explanatory notes were not common practice. However, in recent decades a shift in this area has occurred. Regulatory authorities concerned with the efficiency of capital allocation in the economies, slowly began to demand higher quality corporate financial disclosures, calling for more transparency in reporting. In the attempt to reduce the informational asymmetry between corporate insiders and outside users, the regulatory bodies started to amend region specific laws, standards, and regulations concerning the minimum content of information to be included in the disclosures. Furthermore, with corporate outsiders becoming more sophisticated and increasing competitiveness in capital markets, the demand for non-financial narrative-based accounts providing meaning to companies' performances has been further supporting the development. Because of this advancement, the amount of textual information contained within the financial disclosures has been growing over the past years, becoming an integral and important part of the corporate financial reporting package. In the general context of corporate periodic accounting disclosures, textual content usually appears in the form of unstructured non-financial information concentrated in managerial narrative section accompanying financial statements as well as in supplementary notes explaining accounting numbers. Here it serves an important and informative role of providing insights on assumptions, methodologies, and events underlying the accounting numbers. Presence of textual content has opened for a broader contextual framework through which management of companies can describe or offer an explanation to recent corporate performances and events related to accounting outcomes. The content elucidated through such a framework is largely discretionary and can be dependent on management's incentives. Nevertheless, it opens for incorporation of qualitative view on the

achievements and perspectives of the company through the eyes of its management, providing outside parties with useful context for the understanding of the reported financial data. Typical examples of an application of such framework, usually appear in managerial narratives accompanying financial statements, such as; directors' report, the chairman's statement, management discussion and analysis (MD&A) or CEO's letter to shareholders. According to Merkl-Davies and Brennan, these qualitative disclosures play an important role in the understanding of corporate performances beyond the reach of accounting numbers, as they convey management's perception and perspective on important corporate events and achievements.¹ Furthermore, information allocated in financial narratives play an important role in mitigating the informational asymmetry, serving as a communicational vehicle between corporate managers and outsiders. Bartlett & Chandler conducted a survey study concerning shareholders readership of the corporate disclosures. Their finding suggested that managerial narrative section of annual reports, and other explanatory narratives included in financial statements, tend to attract wider readership in comparison with pure accounting numbers. Besides, they found that shareholders prefer an overview of the company's financial and operational performances to accurate accounting numbers, and therefore value managerial written narratives as most useful.² Rogers & Grant evaluated how corporate disclosures affect sell-side analysts' coverage of the firms. They found that analysts' reports relied largely on the narrative section of annual reports, specifically concentrated in MD&A section, as the largest single source, accounting for 40% of the cited information.³ Given potential influence of financial disclosures on decision making of corporate outsiders and consequently the allocation of capital in the economy, it is maybe not surprising that the corporate financial disclosures are extensively researched from a variety of perspectives. Recently, research based on quantitative and linguistic textual analysis of corporate disclosures has been again gaining traction in the field of accounting research. Due to technological limitations, early research in the field was primarily based on a manual approach. To derive meaningful insights practitioners had to analyze large bodies of financial text based on manual classification and coding of textual content (see Jones & Shoemaker (1994) for review of the research)⁴. Developments in informational technology, text mining and natural language processing field in last two decades, has opened for broad and more consistent approach concerning the analysis of textual

¹ (Merkl-Davies & Brennan, 2007)

² (Bartlett & Chandler, 1997)

³ (Rogers & Grant, 1997)

⁴ (Jones & Shoemaker, 1994)

content. Automated processes have largely been replacing labor-intensive manual content analysis, making room for more complex and innovative approaches in the research field. Following technological advances and development in the accounting research, a growing amount of literature based on computational linguistics analysis of financial disclosures has appeared. The qualitative information contained in financial disclosures has been investigated by researchers with relation to their informational value, through predictive ability research, presentational and readability studies. Feng Li, for example, utilized natural language processing algorithms to examine whether readability of annual corporate disclosures could be associated with persistent earnings of the firm. The results of his research suggested that annual disclosures of firms with lower earnings tend to be more difficult to read. The management of poor performing firms may be acting on incentives of self-preservation, thus resorting to the obfuscation of unfavorable information in public disclosures. Making the disclosures both longer and more verbally complex when compared with better performing firms.⁵ In another study, Feng Li applied integrated dictionary classification algorithm to investigate the relationship between risks sentiments conveyed in firms annual disclosures and its association with future earnings. The results suggested that in a cross-sectional setting, risk sentiment conveyed in the annual disclosures of U.S. registered firms, can to a degree be predictive of firms' lower future earnings.⁶ Nelson and Pritchard, used a similar computational approach when analyzing the connection between litigious risks and the use of cautionary language in financial disclosures of U.S. corporations. Their findings implied that firms, who are subject to great litigation risk from shareholders or authorities, disclose in more cautionary language, updating the language more from year-to-year, and use language that is more readable.⁷ Feldman, Govindaraj, Livnat, & Segal investigated the informational content of nonfinancial signals in the form of tone change conveyed in MD&A narratives. They found that after controlling for accruals and unexpected earnings surprises, the change in tone significantly correlated with short-window returns around the Securities Exchange Commission (SEC) filing dates. Furthermore, they were able to show that tone change, also significantly correlated with drift in excess return after the announcement.⁸ Suggesting that there is a significant association between market reaction and the non-financial textual content of corporate disclosures. Brown & Tucker also researched the informative usefulness of MD&A narratives. By introducing a

⁵ (Li, Annual report readability, current earnings, and earnings persistence, 2008)

⁶ (Li, Do Stock Market Investors Understand the Risk Sentiment of Corporate Annual Reports?, 2006)

⁷ (Nelson, 2007)

⁸ (Feldman, Govindaraj, Livnat, & Segal, 2010)

change measure based on year-over-year similarities in the textual content of MD&A section, they found that U.S. registered firms that experience large economic changes during a period, modify the MD&A section more than those who experience smaller changes. Furthermore, they found that magnitude of stock price response to 10-K filings of the firms is positively associated with the MD&A modification score.⁹ Suggesting that informational content concentrated in firms MD&A section of corporate disclosures is likely to be the function of firm's performance and further supporting the argument that content of the MD&A section can carry informational value relevant to future earnings. It is therefore not surprising that the lion's share of textual-accounting research falls on analysis of managerial narratives and their informational relevance (see Cole & Jones for research review)¹⁰. With most of the research in the field focused on some specific area of financial narratives. Trying to measure the implication of tone, complexity or transparency of written disclosures on future earnings or stock prices of the firm, Cohen, Malloy, & Nguyen used a slightly different approach in their research on the informational value of textual content. Their study proposed tracking changes to the overall textual content of financial disclosures by measuring the year-over-year similarity between them. One of the major findings in their paper suggested that *"the U.S. registered corporations that make significant changes to the textual content of financial disclosures in a given period, as compared to previous, are likely to experience lower returns in the future."*¹¹ The literature concerning textual analysis area of accounting research appears to be focused mainly on U.S. registered firms. The reason for this may lie in both large market capitalization of firms and availability of relevant data through the Securities and Exchange Commission (SEC) register. SEC database (Edgar), among others, contains digital versions of U.S. registered historical financial reports of the firms dating back to 1984, providing researchers with an abundant amount of easily accessible historical data. Considering almost non-existing research in this field for Norwegian registered corporations, the finding of Cohen et al. intrigued us to investigate whether it is possible to detect and measure similar relations between year-over-year changes to corporate disclosures and future stock returns in the Norwegian equity market considering cultural and region-specific differences.

⁹ (Brown & Tucker, 2011)

¹⁰ (Cole & Jones, 2005)

¹¹ (Cohen, Malloy, & Nguyen, 2016)

1.2 The Scope of Research

Our research question originates in the earlier findings of Cohen et al. and carries an exploratory character relative to the Norwegian equity market. From a methodological viewpoint, the original paper by Cohen et al. is the primary motivation for our thesis, although many additional adjustments had to be made considering region-specific cultural and reporting environment. In the original research paper published by authors, it was proposed that it might be possible for investors to obtain abnormal returns by taking on the effort of tracking changes to the textual content of periodic regulatory filing issued by U.S corporations. The research was based on the interesting assumption of the default behavior of the corporate agents. Particularly, that the agents tend to report the same information to the market with a minimum amount of alternation unless there is an expectation of some substantial deviation from current performances. Tracking such changes to textual content could offer the way to detect and reveal information relevant to future firm performance not yet reflected in market prices.¹² According to Hirshleifer and Teoh, textual information has a higher processing cost than numerical content. Such extra processing cost in tracking changes may have implications on the rationale underlying market efficiency hypothesis, as the cost of accessing this information may hamper instantaneous reflection of it in the market.¹³ In this context, we want to examine whether year-over-year changes in the textual content of corporate disclosures for the Norwegian listed firms carry any informational value that may be predictive of subsequent short-term returns.

We hypothesize that substantial textual and structural changes in periodic financial disclosures can carry an informational value that may have implication on the subsequent short-term returns.

Furthermore, we want to investigate whether the change in sentiment conveyed through financial disclosures may have implication on the subsequent short-term returns.

Additionally, we want to examine the role of sentiment as a driving force behind textual and structural changes to corporate financial disclosures.

¹² (Cohen, Malloy, & Nguyen, 2016)

¹³ (Hirshleifer, 2003)

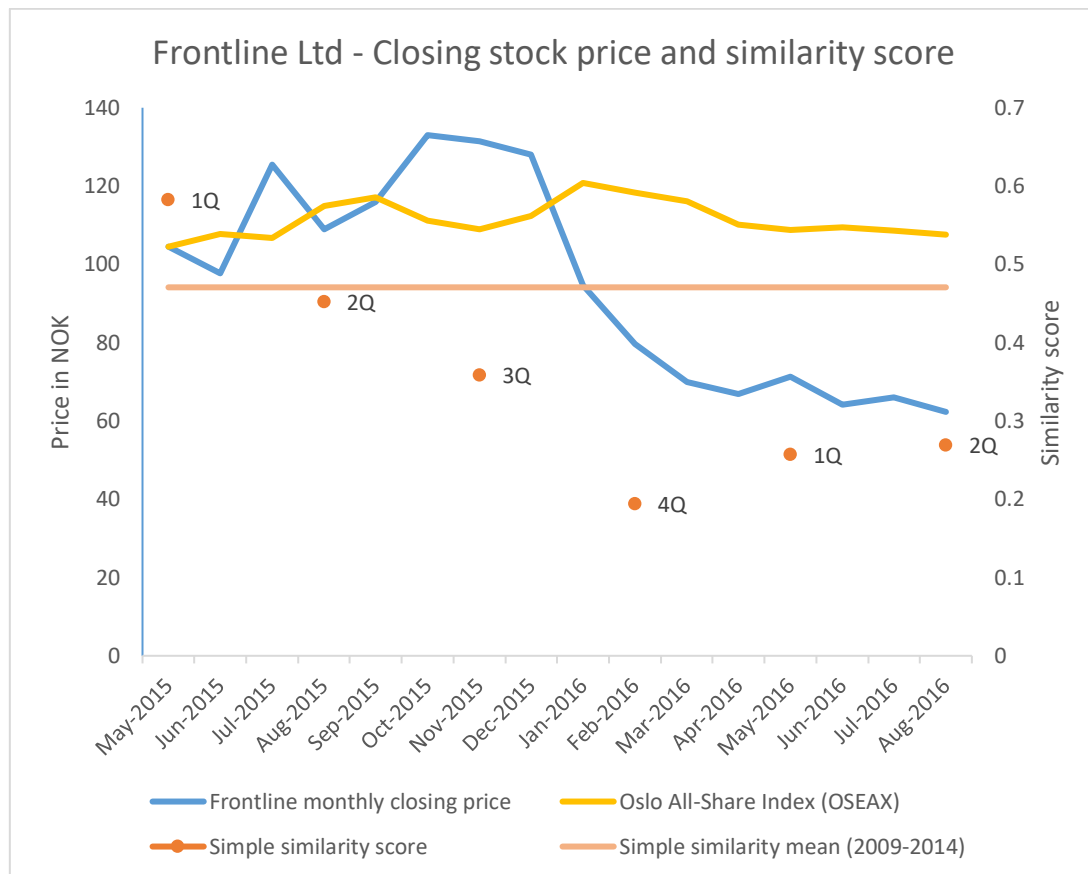
To provide a more intuitive understanding of our approach, consider the example of Frontline Ltd. Frontline Ltd is a shipping company that operates crude oil and product tankers. Prior to November 2015, they had experienced relatively good returns and had historically stable reporting practice concerning year-to-year similarity between the textual content of financial disclosures. While the shipping sector can be somewhat volatile, everything seemed to indicate positive returns for the shareholders. However, looking closer at the 3Q report released November 2015 and 4Q from February 2016 might suggest changes ahead. The two reports had changed substantially from the previous years in terms of textual similarity and contained an increase in words related to litigiousness and uncertainty. Investigating the cause of these changes, we make two findings. First, the third quarter report included news about an agreement to complete a reverse merger with Frontline 2012, an unlisted firm that was created in a previous restructuring process of Frontline Ltd. Such news is often followed by increased volatility and a drop in the share price of the acquirer. This was also the case for Frontline Ltd, where Frontline 2012 was by some perceived as the winning shareholders.¹⁴ This kind of news describes a future event relevant to the investors which are not yet been incorporated into the numerical content of the accounts. Secondly, the fourth quarter report, which was published after the successful merger, contained more words linked to uncertainty and litigiousness compared to the previous year report, more specifically, information about changing market conditions and troubled dealings. One example of the changing market can be found in a comment by the CEO, who states, “*We remain of the opinion that 2017 will see pressure on freight rates as further newbuilding’s are delivered.*” This statement can be categorized as a current snapshot of the shipping market view. Furthermore, in the same report, there are several comments about frustration regarding a failed acquisition of Double Hull Tankers Inc, a proposed stock-for-stock transaction that was declined by the board of the target company. This information is of new, but historical character and indicates the competitor’s view on the frontline stock value. Following these changes in reporting behavior, the Frontline Ltd stock experienced a drop in the share price from 132 NOK per share at the end of November to 71 NOK in May. The 46% decrease in shareholder value over a period of 6 months (see **Figure 1**). This drop was in the media credited mainly to an increase in the capacity of the shipping sector and the failed acquisition, causing profits and share value to drop. Both pieces of information that are credited to the stock decline could be found conveyed in the reports and were significant contributors to the unexpected substantial change in reporting behavior. Could

¹⁴ (SKIPSREVVYEN, 2015)

the deviation from commonly used language and the subsequent stock decline indicate a pattern for predicting future stock returns? We aim to investigate whether there is a relationship between such reporting changes and stock prices in the Norwegian equity market, and thus seek to improve the understanding of the informative usefulness of the changes to the textual content in annual and quarterly reports.

Figure 1: Frontline Ltd. stock price and the similarity scores

The Simple similarity score represented by orange dots is calculated by comparing the labeled type of financial disclosure with the previous year disclosure for the same period, the closer to 1 the more similar are the disclosures. Simple similarity mean is the average similarity score for compared reports prior to 2015. The blue line is the monthly closing prices of Frontline Ltd. OSEAX illustrates the market development during the same period.



Our research question should be of interest to investment fund managers, management of firms listed on Norwegian Stock Exchange and researchers within accounting research focused on Norwegian firms. For example, fund managers of index funds tilted for improved returns (factor funds) can potentially use the findings as a tool to adjust a baseline portfolio, while

agents that are involved in the reporting practice could become more aware of what signals are conveyed through their reporting behavior to investors.

Our approach is based on the quantitative methodology applied to the qualitative textual content. Specifically, we employ a variety of textual analysis approaches measuring year-over-year changes in similarity and sentiment (tone) of textual content in publicly available periodic financial disclosures. By comparing individual firm disclosures pairwise with prior year's disclosures that lines up with the disclosures in question (for example, 1Q-2008 is compared concerning its similarity to 1Q-2007 of the same firm, 2Q-2008 to 2Q-2007 or annual 2009 is compared to annual 2008) we assign them appropriate similarity score. Based on the Master Dictionary developed by Loughran & McDonald¹⁵, we measure the year-over-year change in sentiments conveyed in financial disclosures and assign them appropriate scores. The similarity and sentiment scores for individual firms are then used as explanatory variables in an Ordinary Least Square regression (OLS) where aggregated three-month excess returns of individual firms are the explained variable. To account for initial market reaction concerning the disclosures of the accounting numbers in financial reports, we introduce one-month lag when computing aggregated three-month returns. Meaning that when calculating subsequent returns following the announcement, the starting point is the beginning of the first month after the publication of the financial disclosures. Besides, we control the OLS regression for known stock price predictors such as Norwegian multifactor models. This is done to reassure that potential findings are not just a residual already incorporated into known predictors. The period under the scope of this thesis stretches over approximately ten years, starting with 1Q-2007 and ending with 3Q-2017. The empirical analysis is based on a sample of 48 Norwegian listed firms that is balanced across industrial sectors and is of representative size to that of the Norwegian stock market. To the best of our knowledge, similar research has not been conducted on firms listed at the Oslo Stock Exchange.

1.3 Outline of This Paper

In section 2 we introduce the Oslo Stock Exchange and give a short description of the market size on the global scale and present the Norwegian market composition divided by sectors. Section 3 offers a brief historical introduction concerning the region-specific corporate reporting regulations, as well as providing the general overview of laws, regulations, and standards guarding the corporate disclosure practices of interest. Section 4 concerns the

¹⁵ (McDonald, University of Notre Dame, 2015)

methodology that we have used in our research as well as the presentation of the process when obtaining the sample. When explaining the process, we wish to balance between detail and practicality to give the reader understanding of how and why specific sources and techniques are used, and what obstacles pursuing researchers might encounter. Further, in the same section, we discuss the creation and the origin of the explained and explanatory variables, how they created and why they are used. Lastly, we go through the diagnostics of our dataset to assure the quality and justify the econometric model applied. In section 5, we present the empirical results of our analysis. In section 6, we analyze the result of our research. In section 7, we briefly discuss the implication of the empirical result. Further, we assess the strength and weaknesses of our thesis, pointing out the suggestions for further relevant research and shortly summarize our main findings.

2. The Oslo Stock Exchange

2.1 History and Size

Oslo Stock Exchange was first founded in 1819 and is currently the only independent Nordic stock exchange. The exchange consists of three marketplaces Oslo Børs, Oslo Axess, and Merkur Market. Both Oslo Børs and Oslo Axess are fully authorized and regulated marketplaces. However, only Oslo Børs executes stock listings in accordance to both international requirements and the Norwegian Stock Exchange legislation. Merkur market is a multilateral trading facility with more straightforward requirements and reporting obligations intended for companies with small market capitalization.¹⁶ In May 2017, Oslo Børs had a market capitalization of 2,156 billion NOK.¹⁷ In comparison with members of the World Federation Exchanges, based on market capitalization, it was ranked 29th out of 57 exchanges. On a global scale, Oslo Børs makes up about 0.34% of the world's capital market, making the exchange a relatively small player in a global context.¹⁸

2.2 Sector Representation on the Oslo Børs

The Global Industry Classification Standard (GICS), developed by Morgan Stanley Capital International (MSCI) and Standard & Poor (S&P), is a classification system that classifies

¹⁶ (Oslo Børs, 2018)

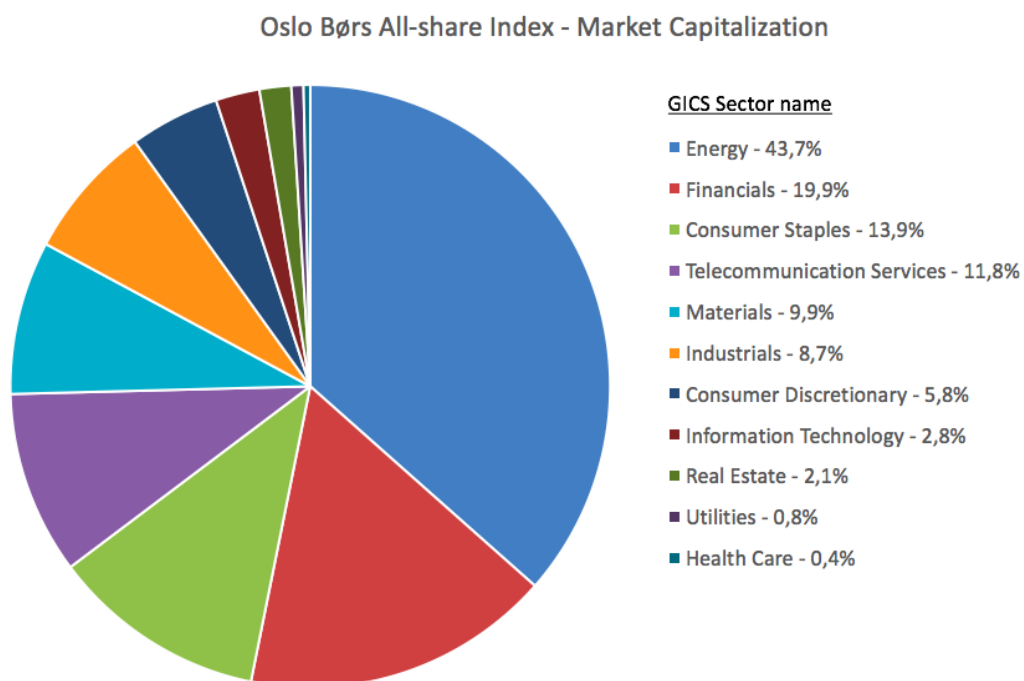
¹⁷ (Oslo Børs, 2017)

¹⁸ (Exchanges, 2017)

listed companies into 11 sectors, 24 industry groups, 68 industries and 157 sub-industries.¹⁹

Figure 2 shows sector representation on Oslo Børs. While the historical barriers between many industries currently are disintegrating due to increased diversification of businesses, the figure nevertheless, provides a reasonable estimate of Oslo Børs marketplace exposure to different areas. As it appears from the diagram Oslo Børs is heavily weighted towards the energy sector, which represents 43,7% of the total market capitalization. Other notable industries include financials and consumer staples with 33,8% of total market capitalization. Consumer staples consist primarily of salmon farming companies but also includes a wine and spirit distributor Arcus.

Figure 2 Oslo Børs All-share Index, Market Capitalization by sector (Thompson Reuters Eikon, 2018)



¹⁹ (MSCI, 2018)

3. Reporting Regulations

In the countries with well-developed and regulated capital markets, companies issue fiscal and periodic financial disclosures intended for the outside parties such as investors, creditors and the public. The form and content of the disclosures are generally governed by some sort of region-specific accounting framework or reporting standards. The framework and standards intended to ensure that relevant financial information is presented in a structured and easy to comprehend configuration, providing outside parties with a reliable source of information about the performance of the companies. In this way, the reporting regulation seeks to reduce the informational gap between management of the companies and corporate outsiders, providing the information that enables outsiders to make reasonable opinions and decisions about potential investments and risks associated with them.

The Norwegian accounting principles have been subject to substantial fundamental changes during the last decades. Early Norwegian accounting rules, dating back to 1874, were mainly concerned with creditor protection-oriented view on accounting. Gradually, tax valuation rules and conservatism principle took over as essential characteristics of legal rules concerning accounting in Norway. During the 1980s there was considerable discussion regarding the linkage between tax and accounting, resulting in new accounting treatments that progressively reduced such linkage. As the result of development in accounting principles and to harmonize Norwegian accounting rules with international practices the Norwegian Accounting Act (NAA) was considerably changed in 1992 and then again in 1998. To better understand the recent requirements in financial reporting regulations for Norwegian listed companies concerning period under the scope, we will in this section give a brief overview of the relevant acts, accounting standards and laws that affect content and reporting practices of companies and their financial disclosures in Norway.

3.1 Norway and European Union

Although not a member of the European Union (EU), Norway has been active members and participants in European Free Trade Association (EFTA) since its early establishment in the 1960s. With further development of EU, most of the neighboring countries and early EFTA members have been embedded as equitable members of the European Union. Accounting for that all the neighboring nations and key trading partners were now a part of EU, and to ensure further free trade and competitiveness of Norwegian goods and markets, active from 1994, Norway entered the European Economic Area Agreement (EEA). The primary goal of the EEA

is to ensure a free flow of goods, people, services and capital between all 31 EEA member states and thus to establish a single inner market for the European area. Further, the agreement intends to ensure non-discrimination, equal rules for competition and equal access to the single inner capital market throughout the EEA. This entails that the internal market must be based on the common regulatory framework, set by an international standard-setting body, and should be practiced equally throughout all of EEA states. Meaning, that when the European Union adopts regulations or laws regarding the internal market, these must also be adopted into the EEA agreement and thus into the legislation of all member states.²⁰

3.2 IFRS and European Single Market

International Financial Reporting Standards (IFRS) previously known as IAS (International Accounting Standards) are developed by an independent standard-setting body, the International Accounting Standards Board (IASB). The primary purpose of these standards is to provide a single set of high-quality global accounting standards that bring transparency, ensure quality of financial information and enable international comparability among the firms existing in distinctive capital markets.²¹ IFRS standards provide common accounting practices and language that makes company accounts understandable and comparable across international boundaries, thus encouraging cross-border transactions and the free flow of international capital. Given the accounting diversity in European countries and to accelerate completion of the internal market for financial services in European single market, Council of the EU and The European Parliament in June 2002 adopted IFRS requirements imposing listed companies to prepare their consolidated accounts following IAS/IFRS starting from 2005 and onwards.²² EU's drive towards global standards in the financial accounting field was viewed as desirable by both companies and investors, as it provided an increase in accounting information value due to harmonization towards the "fair value" model as well as uniformity of style and coverage in financial statements.

3.3 Norwegian Accounting Act and the Introduction of IFRS

Based on Norway's ratification of EEA agreement and obligations following with it, the Norwegian Parliament enacted a new Accounting Act (NAA) that complied with Fourth and Seventh directives (accounting directives) of EU. New NAA is enforced starting from 01 of

²⁰ (Regjeringen, 2017)

²¹ (IFRS Foundation, 2017)

²² (The European Parliament and the the council of the EU, 2002)

January 1999. According to Alexander & Schwencke, the new Accounting Act suggested a broader transition from a credit-oriented Continental perspective on accounting towards a shareholder-oriented Anglo-Saxon view. They argue that the leading indicators of such transition can be in general found in added focus on the information function of financial statements, preference of the matching principal over the prudence in the legal rules and less influence of taxation rules on financial statements.²³

Norwegian Accounting Act (1998) is mainly viewed as a framework law that lays down basic accounting principles and assessment of rules. The primary purpose of the Accounting Act *is to contribute to informative and standardized accounts so that the users of the accounts receive the necessary information (N.B. authors translation)*²⁴, and in that manner concerns only annual accounts and disclosures. Meaning that NAA does not, in particular, regulates requirements for interim reporting practice but lays down general accounting methodology. However, since enactment, the Norwegian Accounting Act has been changed and modified several times to implement new legislative directives and regulations from EU. Because Norway is not part of the EU, and interaction happens through EEA, the legal process of adopting new directives has an extra layer, entailing that separate bylaws and regulations are necessary to adopt as supplements to the original national act. One of the significant bylaws that may have relevance to this paper is the Law of 10 December 2004 No. 81 on amendments to the Act of 17 July 1998 No. 56 on Annual Accounts (implementation of EEA rules for applying International Accounting Standards)²⁵. This new law addition stated that effective of 1 January 2005, all Norwegian listed companies who prepare consolidated annual financial accounts are required to do so following International Financial Reporting Standards (IFRS), issued by International Accounting Standard Board (IASB). Entities that did not prepare consolidated statements was however granted general access to comply with IFRS in their accounting practices if they choose to do so. Such addition to existing legislation can be viewed as the beginning of the widespread introduction of Norwegian companies to IFRS standards. However, companies with listed bond-loans and enterprises using US GAAP standards was given the opportunity to postpone adoption of IFRS until 2007. Consequently, at the beginning of 2005, all except 12 cross-listed companies listed on the Norwegian stock exchange followed IFRS standards for their consolidated annual accounts. Furthermore, the official requirement

²³ (Alexander & Schwencke, 2003)

²⁴ (Stortinget, 1998)

²⁵ (Finansdepartementet, 2004)

concerning the IFRS reporting standards for companies that do not prepare consolidated accounts was first required starting from 1. of January 2011.

3.4 Norwegian Securities Trading Act

Norwegian Accounting Act discussed in the section above forms the starting point for the accounting and financial reporting of the Norwegian listed companies. Norwegian Securities Trading Act (NSTA) however, among other things, sets additional requirements for the annual and semi-annual financial disclosures. The purpose of the NSTA is to *facilitate effective, safe and organized trading in the financial instruments in the Norwegian equity market (N.B. authors translation)*.²⁶ The NSTA concerns regulations in preparation of both annual and semi-annual accounts and disclosures for companies listed in Norway. According to the Securities Trading Act § 5-5. and § 5-6., entities that prepare their consolidated annual financial statements in accordance to IFRS should also prepare semiannual disclosures in accordance to the same international standard. Furthermore, the Act also includes a description of a minimum required informational content in annual disclosures imposed by law. Such that companies are obliged to include *information about important events during the accounting period and their influence on the financial statement as well as the description of the most central risk and uncertainty factors facing the business in the next accounting period (N.B. authors translation)*.²⁷

3.5 Regulation to the Securities Trading Act

This regulation provides additional provision to the original NSTA mentioned above. Starting from 1999 and according to the Regulation to the Securities Trading Act §5-5²⁸, companies listed on Oslo Stock Exchange were required to report their financial position on the quarterly basis in addition to annual and semiannual reporting. However, this requirement was recently canceled, starting from 1st of January 2017, such that listed firms are obligated to publish only annual and half-year reports from 2017 and onwards. This implies that during the period that is under the scope of this paper, quarterly reporting of financial position was imposed by law. However, even though quarterly reporting is no longer mandatory, Oslo Børs Investor Relations advises companies to continue with quarterly disclosure practices onwards. Judging by the amount of published quarterly disclosures for the fiscal year 2017, many companies

²⁶ (Finansdepartementet, 2007)

²⁷ (Finansdepartementet, 2018)

²⁸ (Finansdepartementet, 2007)

indicate that they will continue to issue quarterly financial statements to keep good investor relations.

3.6 Norwegian Accounting Standards

The Norwegian Accounting Standards Board (NASB) founded in 1989 has the primary aim to develop, interpret and publish national and international accounting standards and actively disseminate knowledge about such standards. Accounting standards issued by NASB are to a degree based on international accounting standards (IAS/IFRS) but also offer some national solutions, specifying solutions in several different areas and are supplementary to the original NAA. One of the areas, relevant to this paper, is concerning interim reporting regulations for the Norwegian registered companies. Norwegian Accounting Standard 11²⁹ (NAS 11) based on IAS/IFRS 34³⁰, about interim reporting, required that starting from 2011, all Norwegian listed companies are obliged to prepare their interim reporting in accordance to IFRS standards, as well as stating the minimum number of explanatory notes and information that have to be included in such statements. The IFRS based standards, in general, are characterized by extensively detailed regulations that result in more detailed requirements regarding notes in financial disclosures. Such that, the financial disclosure must provide sufficient information on which assumptions and methods they are based on.

3.7 Conclusion

As it appears from the section above, Norwegian legislative requirements regarding financial disclosures and reporting practices have several layers that are composed of laws, regulations, and standards associated with them. The main conclusion that we want to draw from this is that although ever changing to comply with new EU transparency directives, there is a presence of standardized reporting framework for Norwegian listed companies regarding their financial accounting and reporting practices. Furthermore, the accounting practices for the majority of listed companies are primarily conducted following the requirements of IFRS during the period under the scope of this paper. Although these requirements do not prescribe a standard layout for financial disclosures, they do include a list of the minimum amount of information that should be presented. Therefore, guaranteeing the minimum amount of information and content

²⁹ (Norsk RegnskapsStiftelse, 2011)

³⁰ (IASPlus, 1999)

consistency of companies' financial disclosures. We consider this as an important component to the subject that we are looking into and that it has relevance to the scope of this paper.

4. Approach

4.1 Quantitative Method

Our choice of method is quantitative. We apply a variety of mining, cleansing and computational techniques to handle the large number of text-files and to ensure equal treatment of the data. Furthermore, we apply the econometrical approach, namely Ordinary Least Squares regression (OLS), to investigate the relationships between the variables. The significance threshold is set at 95% confidence level.

4.2 Population & Sample

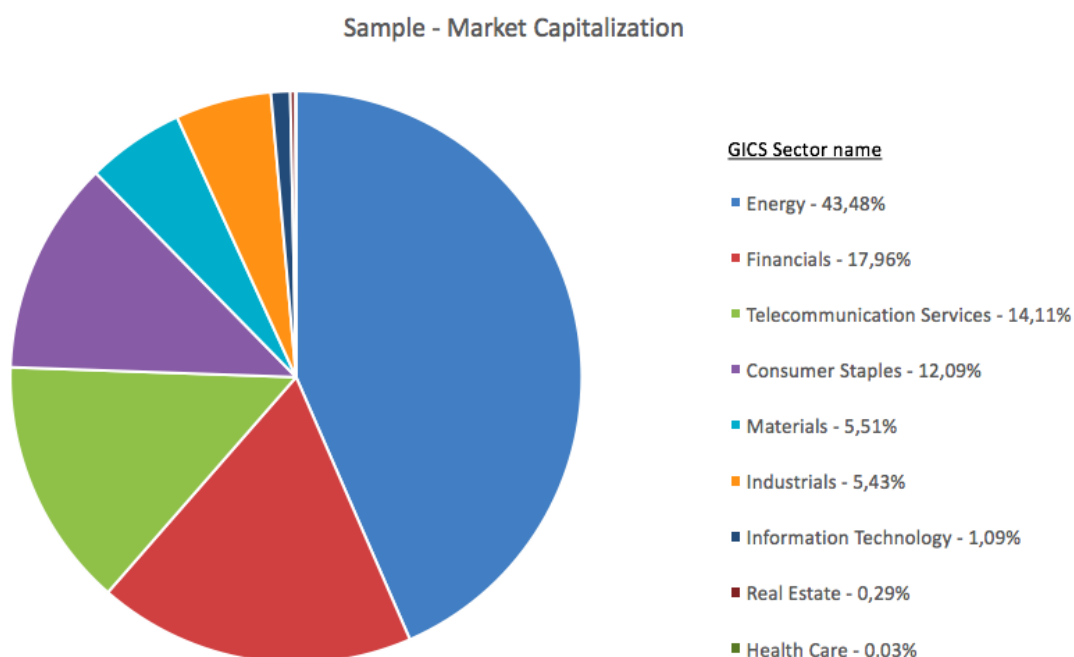
The scope of our research focuses on the companies listed at Oslo Stock Exchange's, more specifically Oslo Børs. In January of 2018, there were 193 active listings in this segment of the Norwegian capital market. Considering that the English language is not native to this part of Europe, a trade-off had to be made when drawing the research sample. The main criteria underlying sample was based on the language of the financial disclosures, preferably English, and the availability of historical financial disclosures. Based on this, a sample of 48 firms was drawn from the listed companies. Reports written in the English language enabled us to utilize the existing sentiment wordlist created by Loughran & McDonald³¹. The application of this dictionary is one of the essential parts of our research, and to our knowledge, there is no such equivalent based on the Norwegian language.

Figure 3 graphically represents the distribution of the sample between the GICS classified sectors. When comparing the **Figure 3** with the **Figure 2**, we note the following similarities and differences in the sample compared to Oslo All-share Index: (OSEAX).

For the three largest sectors, we note that Energy with 43.4% of the sample market capitalization deviates from the index by 0.2%, the Financial sector with 17.9% deviates by 1.9% and telecommunication sector with 14.11% deviates by 2.3%. Considering all sectors, we note that the overall deviation of our sample when compared to OSEAX is approximately 17%.

³¹ (McDonald, University of Notre Dame, 2015)

Figure 3: Sample, market capitalization by sector (Thompson Reuters Eikon, 2018).



In general, we can see that the firms included in our sample capture most of the sector composition in the Norwegian capital market with only small deviations in the most significant sectors. Considering we only sample firms with available reports in the English language and close to complete history in the period under the scope. We are satisfied with the obtained representativeness and that the sample it is not significantly different from the overall market. Given the similarity in sector representation, we assume that our sample is representative of the overall population of Oslo Børs.

4.3 Raw Data Collection and Variables Creation

4.3.1 Data Sources

The primary source of raw data collection related to our research is through the online database "Newsweb.no." This database is one of the additional services offered by Oslo Stock Exchange and is the place where firm-specific public news and financial disclosures are stored and distributed in accordance to requirements of the Security Trading Act §5-12.³², about information dissemination. However, throughout the data collection process, we experienced that this database was in some cases insufficient for our purposes, as some financial disclosures were omitted or missing. To ensure representativeness of our sample some additional actions

³² (Finansdepartementet, 2010)

were taken. We retrieved some of the missing disclosures from the Investor Relation (IR) section at websites of the individual firms. We also found it necessary to send inquiries to nine different companies that did not provide the disclosures of interest online. Lack of a strongly regulated centralized database for firm relevant financial disclosures has to a degree hampered our raw data collection and resulted in a time-consuming process. All financial disclosures for the sample firms were published in Portable Document Format (PDF) and had to be downloaded manually. Publishing dates for each disclosure were then retrieved from the individual files. Financial disclosures were sorted by firm names and publishing dates. This adversity in raw data accessibility may, to some extent, have limited the number of firms that we were able to include in our sample.

4.3.2 Text Mining

As mentioned above, all financial disclosures were initially published in PDF format, containing massive graphical layouts, graphs, and tables with financial information in addition to textual-content. To investigate the textual content of the disclosures, we had to convert the PDF files. Initially, we were considering appliance of common re-formatting tools that uses Optical Character Recognition technology (OCR). As the name implies, the OCR approach involves algorithms that convert the image of typed or handwritten text into machine-encoded text. However, this approach turned out to have a low level of accuracy when transforming PDF to text, as some words were not recognized or misspelled. To account for occurrences of such errors and to ensure consistency of informational content, we chose to utilize the command plugin “xpdf” in statistical software R. This plugin function has an advantage over common tools that uses OCR, as it allows to read the text in files directly from the source transforming it to open text while disregarding all other graphical content. This approach avoids loss of information that quite commonly occurs due to misinterpretation by OCR and allows us to transform PDF files into a standard text document, (.txt) format.

4.3.3 Text Cleaning

Next step in preparing the data for the further analysis was to remove all unnecessary noise. All re-formatted text files contained various amount of noise from the conversion. Some examples of such noise are non-textual characters such as remaining numbers and special characters that needed to be removed to isolate the textual content with informational value. Our solution to this issue was to create a “search and replace” -script in the programing

language Python that deleted or replaced terms found in our list of noisy characters. Only characters that were safe to remove without compromising informational content were omitted.

4.3.4 Quantifying Textual Content

The initial search for a suitable software that could measure the relations of interest turned out not to be a fruitful affair. Although some software packages on the market could potentially apply to our research question, all of them proved to be both costly and little suited for our purposes since many different software programs would be needed to calculate the different measures and relations. Given that existing software's would result in fragmented outputs where vital data may be omitted or inconsistent, we decided on another solution to this issue. To control workflow and to guarantee the reliability and consistency of the output we decided to develop a software customized for our needs in the programming language Python. For this purpose, a programmer with in-depth knowledge and experience in program development was hired to create an algorithm in Python-script, based on our detailed specifications. The developer has been working in close dialogue with us and under our supervision during the programming process to assure applicability and reliability of the software. On completion, the software was rigorously tested in several different contexts to ensure the reliability of the specified measures. The primary function of the software is to compare pairs of text documents to quantify textual content. For example, the textual content of 1Q-2009 is compared with the textual content of the previous year disclosure 1Q-2008, the textual content of annual disclosure dating from 2009 is compared to the textual content of 2008, where the same methodology applies for all types of quarterly and annual financial disclosures in the ten-year period starting from 2007. The software then calculates the four different similarity scores between documents. Additionally, the software calculates sentiments change scores through integration with sentiment wordlist. In this manner, the software compares and calculate the similarity scores (measures) specified below across all documents. The output from software comes out in two separate csv. files. The primary output included all the specified similarities measures and publishing dates of the newest disclosure in the pair compared. The secondary output is more of a descriptive nature and is used to determine the amount or the size of textual information present in the text files. Descriptive output enabled us to check text documents for errors and alleviated the detection of issues occurring in the context of PDF to text conversion.

4.4 Similarity measures

Development in computer science field, computational linguistics, and Natural Language Processing (NLP) in recent decades offers a wide range of approaches on how to detect and measure textual similarity across a variety of documents in large datasets. Such approaches are usually based on some form of machine learning algorithms that are trying to mimic human decision-making behavior. Although there are many choices of different approaches, there is no universal standard on which approach will give the most reliable results, and the choice therefore often depends on what type of relationship one tries to measure. Many of the popular measurements are based on the inverse of the distance between two or more documents, where high numbers indicate high similarity and lower number implies dissimilarity. In the textual context, algorithms are usually based on a heuristic approach such as character or term counting and frequency analysis. Conventional area of application for such machine learning algorithms is in the detection of similarity in plagiarism control, web scraping, and clustering.

4.4.1 Cosine Similarity

Cosine similarity between two text documents gives us a measure of how similar these documents are to each other concerning their subject matter. This similarity measure does so by counting the number of words occurring in both documents, words in common, but ignoring the word order and the size of the documents. The cosine similarity can be defined as *a measure of similarity between two non-zero vectors of an inner product space that measures the cosine of the angle between them*. The cosine angle between two vectors of $0^\circ = 1$, meaning that they are pointing in the same direction and therefore similar to each other, and is > 1 for any other angle in the interval. Cosine similarity between two documents A and B is the judgment of orientation of their vectors but not the magnitude, as the cosine measure takes the norm of the vectors and thus get rid of the influence of the size.

This measure is computed as follow: let A_s and B_s be the set of terms occurring in A and B respectively. Define T as the union of A_s and B_s , and let t_i be the i^{th} element of T . We then define the term frequency vectors of A and B as:

$$\begin{aligned} A^{TF} &= [nA_s(t_1), nA_s(t_2), \dots, nA_s(t_n)] \\ B^{TF} &= [nB_s(t_1), nB_s(t_2), \dots, nB_s(t_n)] \end{aligned}$$

Where $nA_s(t_1)$ is the number of occurrences of term t_i in A , and consequently $nB_s(t_1)$ is the number of occurrences of term t_i in B . Then, by applying and rearranging the dot product formula from vector calculus, $A^{TF} \bullet B^{TF} = \|A^{TF}\| * \|B^{TF}\| * \cos(\theta)$, the cosine similarity between two documents can be defined as:

$$Sim\ Cosine = \cos(\theta) = \frac{A^{TF} \bullet B^{TF}}{\|A^{TF}\| * \|B^{TF}\|} = \frac{\sum_{i=1}^n A^{TF} B^{TF}}{\sqrt{\sum_{i=1}^n (A^{TF})^2} \sqrt{\sum_{i=1}^n (B^{TF})^2}}$$

Where the dot product (\bullet), is the scalar product and $\| \ \|$ is the Euclidian norm.

For a more intuitive understanding of the Cosine similarity measure, we provide a simple textual and numerical example. Consider these three short texts:

A: We expect growth in revenues

B: We expect further growth in revenues

C: We expect decrease in sales

From the visual comparison between these texts, we can see that A is similar to B and that A is more similar to B than it is to C . To quantify similarities between these texts we calculate the cosine similarity as follow:

We define the union T of A and B as:

$$T(A,B) = [we, expect, further, growth, in, revenues]$$

The term frequency vectors of A and B are:

$$A^{TF} = [1, 1, 0, 1, 1, 1]$$

$$B^{TF} = [1, 1, 1, 1, 1, 1]$$

The cosine similarity score of A and B is therefore:

$$Sim\ Cosine(A, B) = \frac{\sum_{i=1}^n A^{TF} B^{TF}}{\sqrt{\sum_{i=1}^n (A^{TF})^2} \sqrt{\sum_{i=1}^n (B^{TF})^2}} = \frac{(1 * 1 + 1 * 1 + 0 * 1 + 1 * 1 + 1 * 1 + 1 * 1)}{\sqrt{(1^2 + 1^2 + 1^2 + 1^2 + 1^2)} * \sqrt{(1^2 + 1^2 + 1^2 + 1^2 + 1^2)}} = 0,91$$

We can also compute the cosine similarity for A and C in a similar manner:

The union T of A and C is:

$$T(A,C) = [we, expect, growth, in, revenues, decrease, sales]$$

The term frequency vectors of A and C are:

$$A^{TF} = [1, 1, 1, 1, 1, 0, 0]$$

$$C^{TF} = [1, 1, 0, 1, 0, 1, 1]$$

The cosine similarity score of A and C is therefore:

$$\begin{aligned} Sim\ Cosine(A, C) &= \frac{\sum_{i=1}^n A^{TF} B^{TF}}{\sqrt{\sum_{i=1}^n (A^{TF})^2} \sqrt{\sum_{i=1}^n (B^{TF})^2}} = \\ &= \frac{(1 * 1 + 1 * 1 + 1 * 0 + 1 * 1 + 1 * 0 + 0 * 1 + 0 * 1)}{\sqrt{(1^2 + 1^2 + 1^2 + 1^2 + 1^2)} * \sqrt{(1^2 + 1^2 + 1^2 + 1^2 + 1^2)}} = 0,6 \end{aligned}$$

From the calculations above, we can see that text A is more similar to B than it is to C , and that cosine similarity measure allows us to capture and quantify these similarities by transforming text documents to vectors.

4.4.2 Jaccard Similarity

In the previous section, we have discussed similarity cosine measure that allows us to quantify the similarity between two documents by transforming them into points or real-valued vectors in Euclidian space and then measuring the degree of angle between them. Jaccard similarity coefficient belongs to the same group of similarity measures as the Cosine similarity mentioned above but applies a different approach in the calculation. Namely, Jaccard similarity calculation does not treat term frequency as the real-valued vector but as binary vectors, the data sets, and is defined as:

$$Sim\ Jaccard = \frac{|A^{TF} \cap B^{TF}|}{|A^{TF} \cup B^{TF}|} = \frac{|A^{TF} \cap B^{TF}|}{|A^{TF}| + |B^{TF}| - |A^{TF} \cap B^{TF}|}$$

Meaning that *the Jaccard coefficient is the size of the intersection of two term frequency sets divided by the size of the union of the same term frequency sets.*

To further clarify the calculation of this similarity measure we can consider the same textual example as mentioned above, the Jaccard similarity is then calculated as follows:

$$Sim\ Jaccard(A, B) = \frac{|\{we, expect, growth, in, revenues\}|}{|\{we, expect, further, growth, in, revenues\}|} = \frac{5}{6} = 0,83$$

So that Jaccard similarity for A and C is then:

$$Sim\ Jaccard(A, C) = \frac{|\{we, expect, in, \}|}{|\{we, expect, growth, in, revenues, decrease, sales\}|} = \frac{3}{7} = 0,42$$

Hence, the Jaccard similarity coefficient can be interpreted as a ratio of the number of words in common for both documents to the number of unique words in both documents and can vary between 0 and 1, where 1 equals completely identical.

4.4.3 Minimum Edit Similarity

Minimum edit distance is the way of quantifying string similarities, text files, and is mainly used in dynamic programming concerning information extraction, speech recognition, and machine translation. The minimum editing distance between two strings is defined as *the minimum number of editing operations, insertion, deletion, substitution, that are needed to transform one string into the other*, and in our case, is calculated as follow:

Sim Minedit =

$$1 - \frac{\text{(smallest number of terms needed to be inserted, deleted or substituted to make texts equal)}}{\text{Total number of terms in both texts}}$$

For more intuitive understanding consider same textual example's A, B, and C as mentioned above. To transform text A into text B requires only one insertion operation of the term "further" where the total amount of terms in both texts is 11 so that minimum editing distance similarity is:

$$1 - \frac{1}{11} = 0,90$$

Transformation of text *A* to text *C* requires deletion of two terms “growth,” “revenue” and insertion of two terms “decrease,” “sales.” With the total amount of terms in both text of 10, we then have that Minedit similarity between *A* and *C* is:

$$1 - \frac{4}{10} = 0.60$$

As we can see, Minedit similarity provides a useful measure of how similar two documents are to each other.

4.4.4 Simple Similarity

In the computation of the Simple similarity measure, we utilize the SequenceMatcher function from Python that allows for side by side comparison of two blocks/documents. The measure is computed by listing terms frequencies for both documents and comparing to each other. The similarity between term frequencies is then normalized as a ratio between (0, 1) where maximum equals similarity and minimum dissimilarity.³³ This approach allows for a side-by-side comparison of changes, additions, and deletions between the “old” and “new” document and is normalized by the size of the “old” document. The Simple Similarity measure is the only measures that capture the order of terms in the documents and therefore offers insight into structural changes between two documents.

4.5 Sentiment Measures

The sentiment is a term that can be *defined as the tone of language, expressing a feeling or emotion conveyed by the words*. Several studies in the field of accounting research have applied different dictionary-based sentiment categories in their research (see Introduction section for an overview). The researchers often classify words into categories of interest or in relation to the phenomenon that they are investigating. The approach is based on subjective beliefs about what sentiment the word is expressing. However, to measure the role of sentiment in its relation to some other factors one must preferably use dictionary adapted to the specific field of research, as some words may carry different sentiments depending on the type of text or field. For instance, in the financial industry words related to risk can carry a different sentiment than that of the fish farming industry. This difference in meaning of sentiments occurs because the

³³ (Python Library Reference, 2006)

risk is often perceived as a fundamental part of business operations in the financial industry. Designed specifically for the use in accounting research, Loughran McDonald has developed a growing Master Dictionary of sentiments based on terms frequently found in public disclosures of companies. The dictionary is an attempt to classify frequently occurring words by six different sentiment categories; Negative, Positive, Uncertainty, Litigious, Modal and Constraining words.³⁴ The classifications are widely used in empirical works and are considered as the foundation for research in the field of textual analysis in accounting and finance.³⁵

In this thesis, we want to apply the general approach of identifying positive and negative sentiment based on the Loughran McDonald Master Dictionary. We wish to measure an overall sentiment change score for the corporate disclosures. We, therefore, consider this dictionary suitable for our purposes, as the dictionary was developed in relation to the authors own research in the field of accounting. Loughran McDonalds Master dictionary was obtained from the Software Repository for accounting and finance³⁶. No alterations to the actual dictionary classifications were made. Based on the Master Dictionary we define our sentiment measure as the change in the number of positively classified terms minus the change in the number of negatively classified terms divided by the size of the change, where the size of the change is the total number of terms added or deleted from old to the new document.

4.6 Stock Returns

To obtain comparable returns adjusted for the interest rate regime of the time, we calculate firm-specific excess returns above the risk-free rate. In our analysis, we will be using excess returns above the risk-free rate as the explained variable. We use monthly forward-looking rates estimates from Norwegian Interbank Offered rate as our risk-free rate of return during the period.

Monthly stock returns were downloaded with Thompson Reuters Datastream using the formula builder "total return parameters." Total return in Datastream is defined as: "*The total return incorporates the price changes and any relevant dividends for the specified period. Compounded daily return for the specified period is used to calculate Total Return and it's effectively the dividend reinvested.*" From the total monthly returns, we calculated arithmetic

³⁴ (McDonald, 2015)

³⁵ (McDonald, Private e-mail correspondance, 2018)

³⁶ (McDonald, 2015)

portfolio return of the returns for a three-month period. Excess returns above the risk-free rate are calculated by subtracting the short-term risk-free rate for the same period.

4.7 Multifactor Model

We will in our regression use a multifactor model to control for additional factors associated with return performance. The Carhart four-factor model is commonly used to explain stock return. The model was developed as an extension to the capital asset pricing model and is based on the finding that certain stock characteristics were found to outperform others. In addition to the Carhart model, we also choose to incorporate a liquidity factor as research in both international and Norwegian context find it to be an important factor affecting the performance of stocks. Our control variables are therefore; market return excess of risk-free rate (Risk premium), High Minus Low book to market ratio (HML), Small Minus Big market capitalization (SMB), Up Minus Down momentum of the stock movement (UMD), and additionally a liquidity factor (LIQ)³⁷ which is calculated by subtracting low spread by high spread.

As the factors are market specific, we download data for the Norwegian stock market. Using monthly data, we gather risk-free rates, market returns, Carhart factors and liquidity factor from the BI financial data webpage that host data from the Oslo Stock Exchange.³⁸ The factors are then transformed from a monthly to a three-month period. The factor returns being arithmetic, are transformed by adding each of the months as logarithmic returns before converting them to arithmetic three-month portfolio returns.

4.8 Data

4.8.1 Data Diagnostics

Given the size of our sample and a significant amount of observation, we want to check our data to verify it and avoid potential problems with inferences of estimated regression coefficients.

As the first step, we wanted to check our variables for potentially influential outliers that may affect our regression results and coefficient estimations. An outlier is an observation with a large residual that may have occurred due to an error in data entry or some other problem that

³⁷ (Randi Næs, 2008)

³⁸ (Ødegaard, 2018)

should be further investigated. We plot our dependent variable against each of the predictor variables in the scatterplot matrix for visual inspection to get an idea of potential problems. From the graph, we were able to see that some observations (data points) for variables were far away from the majority. This indicated a potential problem with observations, which therefore required extra attention. We then regressed the dependent variable on the predictors and computed standardized residuals as a first step in identifying outliers. For further analysis, we plotted standardized residuals on "stem and leaf" plot. As we expected, the plot suggested that we had an outlier problem as residuals absolute value for five observations exceeded a value of $3*$. Further, to identify which of the observation were causing a potential outlier problem, we labeled the standardized residuals and utilized the high-low (Hilo) command in Stata, this provided us with ranking and description of the ten highest and lowest observations. After careful inspection of these observations in the dataset, we could confirm that we had four data entry errors. It is likely that this error had occurred during PDF to text conversion. As the problem was limited to only four of the observations of concern and occurred due to data entry error, we decided on deletion of these observations from the dataset.

4.8.2 Gauss-Markov Theorem

To ensure that estimated coefficients provided by the OLS regression are the Best Linear Unbiased Estimators (BLUE), in this section, we want to go through the Gauss-Markov theorem assumptions.

To check the assumption of Linearity in parameters, we plot all our measures one by one in an augmented component-plus-residual plot for visual inspection. All similarity measures and sentiment came out to be close to linear, and we conclude that the assumption is met.

The assumption of Normality in multiple regression concerns the requirement of the normal distribution of errors terms in the relationship between the explanatory and dependent variables. In this context, a possible violation of the normality assumption does not contribute to inefficiency or bias of the regression model but will bias the estimation of standard errors, and hence confidence intervals and p -values for significance testing. However, when the sample size is sufficiently large, in our case 2282 observations, the normality is assumed by the Central Limit Theorem (CLT). The distribution of the error terms will approximate normality in the large sample so that we consider the error terms to be asymptotically distributed.

Homoscedasticity assumption about the homogeneity of variance is stating that the variance of unobserved error (u), around the regression line, is constant given any values of the explanatory variable. Whenever this assumption fails, we can suspect the presence of heteroscedasticity. Meaning, that the variance of the unobserved error term is non-constant around the regression line and OLS estimators for the population coefficients do not have minimum variance. Homogeneity of error terms variance is therefore vital for t and F -tests and thus for justification of confidence intervals construction of the regression estimators. In the presence of heteroscedasticity, the regression estimators of the OLS will still be consistent and unbiased, but the estimated standard errors will be erroneous. Thus, the OLS estimators will no longer be BLUE. To detect violation of the homoscedasticity assumption we used both visual inspection of scatter plots of the error term and numerical tests. As the first step, we visually inspected our data by plotting residuals against fitted values where the graph suggested non-constant variance in the error term. Further, we ran the Breusch-Pagan test to test the null hypothesis of homoscedasticity in the error term. The test result was highly significant with $p > .001$, so the null hypothesis was rejected, and we could confirm the presence of some unknown form of heteroscedasticity in our sample. One of the applied methods of dealing with heteroscedasticity is Weighted Least Squares (WLS). However, this method only applies when the form of heteroscedasticity is known and, in our case, unknown type of heteroscedasticity, we decided on the application of heteroscedasticity-robust standard errors. According to Woolridge³⁹ robust standard errors will account for heteroscedasticity of unknown form in large samples.

Further, we investigate the explanatory variables for high correlation that may cause multicollinearity problems. If present, multicollinearity can be problematic as it can inflate the variance of the coefficients in question, thereby making it more difficult to determine which of the variable is causing the partial effects. This is not breaking any of OLS and is also not an issue for control variables if the coefficients are not of interest. Due to the correlation between the similarity measures, we believe it can be potentially problematic as the measures are created using various computational techniques trying to measure the “same” change. We therefore decided to investigate the variance inflation factor (VIF) of the measures. VIF is the factor that the average variance of the similarity betas is inflated by.

We first run the regression with all the similarity measures included to get the VIF scores.

³⁹ (Woolridge, 2013, p. 269)

Table 1: Variance inflation factor of Similarity measures

	VIF
Sim_Cosine	2.5
Sim_Jaccard	<u>6.4</u>
Sim_Simple	3.2
Sim_Minedit	6.8
Sentiment	1.0
SMB_3M	2.8
HML_3M	1.1
UMD_3M	1.1
LIQ_3M	3.4
RISK_PREM	3.0

Average similarity VIF 4.725

For our similarity measures, the average VIF is 4.7. We consider this to be indicative of a potential multicollinearity problem between our variables. An approach to get correct partial measurements when VIF is large is by increasing the sample size to sufficient degree where one can isolate the effect. Because substantially increasing the sample is not easily done in our case, we decide to solve the multicollinearity issue by using an alternative approach of separate regressions for each of the similarity measures.

5. Empirical Results

5.1 Descriptive Statistics

Table 2: Summary statistics for the analyzed sample.

The table provides a summary statistic for all the quarterly and annual disclosures that have been analyzed. (*N*) refers to the total number of the documents. (*Word count*) is the total number of words present in specific disclosures. (*Mean*) is the average amount of words present in the disclosures. (*SD*) refers to standard deviation from the mean. (*Min*) and (*Max*) refers to the minimum and the maximum amount of word present in each specific group.

	N	Word Count	Mean	SD	Min	Max
All documents	2575	34137822	13257	18413	419	155284
Quarterly	2073	11827157	5705	1913	419	27435
Annual	498	22239467	44658	12040	8583	155284

Table 3: Summary statistics for the four similarity measures and Sentiment.

The table provides a summary statistic for the four similarity measures and Sentiment calculated for the sample. (*N*) refers to the total number of the documents adjusted for the base-year. (*Mean*) is the average of each of the respective measures. (*SD*) refers to the standard deviation from the mean. (*Min*) and (*Max*) refers to the minimum and the maximum of each individual similarity scores calculated for the analyzed documents.

	N	Mean	SD	Min	Max
Sim_Cosine	2282	.9730245	.051088	.4474973	.9995173
Sim_Jaccard	2282	.5883938	.1179755	.153551	.925447
Sim_Simple	2282	.4681673	.1602092	.03353846	.8724108
Sim_Minedit	2282	.7944778	.0965461	.19047619	.9613025
Sentiment	2282	-.0029661	.0388317	-.4890235	.1892361

Table 4: Similarity measures correlation matrix.

The table presents the degree of correlation between four similarity measures. All the measures have high and positive correlation above 0.5 with each other, except Sim_Simple with Sim_Cosine similarity measures which correlate only by .350.

	Sim_Cosine	Sim_Jaccard	Sim_Simple	Sim_Minedit
Sim_Cosine	1			
Sim_Jaccard	0.519	1		
Sim_Simple	0.350	0.810	1	
Sim_Minedit	0.732	0.858	0.704	1

5.2 Main Results

Table 5: Main results – Robust OLS Regression.

The table presents the main results of the regression analysis. Explained variable (*Ln_3Month_Excess*) is defined as three months aggregated returns above the risk-free rate for each of the individual firms in the sample following one month after the publication. *Sim_Cosine*, *Sim_Jaccard*, *Sim_Smple*, *Sim_Minedit*, and *Sentiment* are explanatory variables of main interest and are calculated based on similarity scores between the documents. *DummyA* is a dummy control variable for annual financial disclosures. *Risk_Prem_3M*, *SMB_3M*, *HML_3M*, *UMD_3M*, and *LIQ_3M* are the explanatory control variables based on known stock return predictors. The significance threshold is set at .05

	(1) Ln 3 Month Excess b/p	(2) Ln 3 Month Excess b/p	(3) Ln 3 Month Excess b/p	(4) Ln 3 Month Excess b/p	(5) Ln 3 Month Excess b/p
Sim_Cosine	0.161 (0.16)				
Sim_Jaccard		0.148* (0.01)			
Sim_Simple			0.091* (0.02)		
Sim_Minedit				0.228*** (0.00)	
Sentiment					0.375* (0.04)
DummyA	-0.033* (0.04)	-0.050** (0.00)	-0.040* (0.02)	-0.051** (0.00)	-0.027 (0.09)
RISK_PREM_3M	0.705*** (0.00)	0.676*** (0.00)	0.682*** (0.00)	0.666*** (0.00)	0.703*** (0.00)
SMB_3M	-0.091 (0.39)	-0.091 (0.38)	-0.086 (0.42)	-0.082 (0.43)	-0.095 (0.36)
HML_3M	0.108 (0.12)	0.104 (0.13)	0.106 (0.12)	0.107 (0.12)	0.105 (0.13)
UMD_3M	0.229*** (0.00)	0.222*** (0.00)	0.224*** (0.00)	0.221*** (0.00)	0.223*** (0.00)
LIQ_3M	0.116 (0.36)	0.088 (0.48)	0.088 (0.49)	0.076 (0.54)	0.111 (0.38)
constant	-0.198 (0.07)	-0.125*** (0.00)	-0.083*** (0.00)	-0.219*** (0.00)	-0.042*** (0.00)
R-sqr	0.0563	0.0581	0.0577	0.0601	0.0580
Prob>F	0.0	0.0	0.0	0.0	0.0
n = 2282					

* $p < .05$, ** $p < .01$, *** $p < .001$

5.3 Explaining Changes in Reporting Behavior

Table 6: Mechanism testing – Quarterly reports.

The table presents the results of separate OLS regression for each of the similarity measures calculated for the quarterly financial disclosures. *Sim_Cosine*, *Sim_Jaccard*, *Sim_Smple*, *Sim_Minedit* are the explained variables, where *Sentiment* is defined as the explanatory variable. The significance threshold is set at .05

	(1) Sim_Cosine b/p	(2) Sim_Jaccard b/p	(3) Sim_Simple b/p	(4) Sim_Minedit b/p
Sentiment	0.012 (0.54)	0.228** (0.00)	0.308** (0.01)	0.141** (0.01)
constant	0.967*** (0.00)	0.559*** (0.00)	0.444*** (0.00)	0.774*** (0.00)
R-sqr	0.0000	0.0058	0.0049	0.0027
N	1831	1831	1831	1831
Prob>F	0.5	0.0	0.0	0.0

* $p < .05$, ** $p < .01$, *** $p < .001$

Table 7: Mechanism testing – Annual reports.

The table presents the results of separate OLS regression for each of the similarity measures calculated for the annual financial disclosures. *Sim_Cosine*, *Sim_Jaccard*, *Sim_Smple*, *Sim_Minedit* are the explained variables, where *Sentiment* is defined as the explanatory variable. The significance threshold is set at .05

	(1) Sim_Cosine b/p	(2) Sim_Jaccard b/p	(3) Sim_Simple b/p	(4) Sim_Minedit b/p
Sentiment	-0.013 (0.23)	-0.180* (0.05)	-0.052 (0.69)	0.014 (0.83)
constant	0.991*** (0.00)	0.703*** (0.00)	0.565*** (0.00)	0.872*** (0.00)
R-sqr	0.0002	0.0072	0.0003	0.0001
N	443	443	443	443
Prob>F	0.2	0.0	0.7	0.8

* $p < .05$, ** $p < .01$, *** $p < .001$

5.4 Findings

We find all the regression models in the main results to be statistically significant. *Sentiment* and all the similarity variables except *Sim_Cosine* are statistically significant. The three significant similarity variables are consistent concerning coefficients signs and indicate a relationship where less change imply higher short-term return. The *Sentiment* variable is statistically significant and has a positive beta. Suggesting that positive change in sentiment of firms' disclosures is associated with higher subsequent short-term average returns. *Risk_Prem_3M* is highly statistically significant for all the models, and as expected has a positive sign. Recall that this variable was included as an important control factor to control that our findings are not just driven by the overall exposure to market return.

For the Mechanism testing, the similarity variables *Sim_Jaccard*, *Sim_Simple*, *Sim_Minedit* regressed on *Sentiment* variable for the group with quarterly reports show significance at the 5% level and a positive relationship. *Sim_Cosine* is the only of the similarity measures that is not statistically significant for the quarterly disclosures. For the annual disclosures group, we only find a significant relationship at the 5% level for the *Sim_Jaccard* variable. We note that the sign of the coefficient is negative, which is conflicting with our initial finding for the mechanism in the quarterly disclosures.

6. Analysis

Descriptive statistics

From the summary statistics presented in **Table 2**, we can see that the quarterly disclosures for Norwegian firms analyzed in the sample contain on average 5.705 words, with the smallest disclosure consisting of just 419 words and largest of 27.435. However, we can see that average annual disclosures word count tends to be roughly eight times larger than quarterly, consisting of 44.658 words. Apparently, there tends to be a significant difference between the amount of textual content and the size of the different financial disclosures. Recall that interim financial disclosures are guarded by less strict legal regulations regarding the required amount of information to be included in these statements. While annual financial disclosures are required by law to include a description of significant events, future risk and uncertainty factors that may have implication on firm's performances, the content of interim reports is mainly optional. Additionally, in annual disclosures management of the firms usually reflects on past performances of ended fiscal year, summing it up, and discussing the outlooks of the current

period. Making managements narrative sections substantially larger. Furthermore, since no two firms are entirely alike, the differences in size can also be attributed to differences in the complexity of operations or firm's structure.

Table 3 reports the summary statistics of our four document similarity measures and sentiment scores. As described in the section about the calculation of measures, the similarity measures range between 0 and 1, where 1 indicate total similarity and 0 dissimilarity. We note that *Sim_Cosine* similarity measure has the highest mean (.973) and the least amount of variance (SD =.051) of the four change measures, thus implying that the distribution of this measure is narrow. *Sim_Minedit* also tends to have relatively low variance (SD =.096) when compared to *Sim_Jaccard* and *Sim_Simple* similarity but is centered at a lower level with the mean of (.0794). Recall that the *Sentiment* variable is calculated as the change in the number of positively classified terms minus the change in the number of negatively classified terms divided by the size of the change. Considering the time-period under the scope, with the global financial crisis of 2007-2008 and significant downturn in oil prices in 2014, we assume the distribution of the *Sentiment* measure presented in **Table 3** to be reasonable in these circumstances.

Main results

Table 5 presents the main results of heteroscedasticity robust OLS regression of firm-specific three-month returns (explained variable) following one month after the publication of financial disclosures on our four similarity measures and the sentiment measure (explanatory variables). Additionally, we included the host of known return predictors (*Risk_Prem_3M*, *SMB_3M*, *HML_3M*, *UMD_3M*, and *LIQ_3M*) as explanatory control variables for our regression. From the output, we can see that *SMB_3M*, *HML_3M*, and *LIQ_3M* variables are not statistically significant for all the regressions. To avoid the potential model-over-specification issue, we tested these not significant variables for their joint significance in relation to the models. The null hypothesis was rejected with $p < .001$, meaning that variables are jointly statistically significant and are therefore kept in the models.

Looking at the main results table, we infer that our three similarity measures *Sim_Jaccard*, *Sim_Simple*, and *Sim_Minedit* have a significant and positive relationship. This implies that less change to the textual content of financial disclosures is associated with an increase in three-month subsequent returns. Inverse interpretation of these results suggests that substantial

changes to the structure and textual content is associated with lower subsequent future returns. We also note that one of our measures, namely *Sim_Cosine*, is not statistically significant in the regression model. Remember that each of the similarity measures is calculated with the application of different approaches in how they measure the similarities. For example, the *Sim_Jaccard* similarity is computed as the ratio between the numbers of words in common for the two documents to the number of unique words for the documents. While *Sim_Simple* also measures the order of word and sentences, thus also accounting for the changes in the structure of the disclosures. A possible explanation behind statistical insignificance of the *Sim_Cosine* variable may lie in the narrow distribution of the variable which is affecting significance testing. This narrow distribution can be attributed to the way the measure is calculated. Recall that *Sim_Cosine* similarity measures the amount of word in common in both documents, ignoring the word order and size of documents. In this way, the *Sim_Cosine* similarity measures how similar two documents are to each other concerning their subject matter. As the subject covered in corporate financial disclosures mainly concerns presentation of accounting numbers for the period, it is fair to assume that this measure comes little too short in measuring substantial changes in the overall textual content of the documents. Better application of this measure can be found in measuring similarity in some specific section of financial disclosures, for example, changes to MD&A section. Furthermore, we note that *Sentiment* measure has a significant and positive coefficient, suggesting that shift towards more positively phrased wording in financial disclosures is associated with an increase in the subsequent three-month return.

Given that the measures provide varying scores for the same document pairs we will use change in one standard deviation (SD) for the interpretation of effect. We use the technical interpretation of the Log-Level regression to evaluate the partial effect of the statistically significant variables:

$$\text{Log-Level: } \% \Delta y = 100 * (e^{\beta x} - 1)$$

For example, looking at the different measures and coefficients, we find that if *Sim_Jaccard* decrease by one SD of .1179 we expect the firms' next three-month return above risk-free rate to decrease by 1.88%. Likewise, if *Sim_Simple* similarity decrease by one SD of .1602, we expect the firms' next three-month return above risk-free rate to decrease by 1.53%. Furthermore, if the change in *Sim_Minedit* decrease by one SD of .0965 we expect the firms'

next three-month return above risk-free rate to decrease by 2.47%. Moreover, if the *Sentiment* were to decrease by one SD of .0388, we expect firms' next three-month return above the risk-free rate to decrease by 1.77%.

Considering that annual disclosures, as mentioned earlier, tend to be substantially more extensive regarding the amount of textual content, structure, and size. We include a binary explanatory variable *DummyA* in the regression. The variable differentiates between annual and quarterly financial disclosures where the base group is quarterly. Judging from the regression output, we note that dummy variable *DummyA* is not statistically significant in the regression output (#5). This implies that we cannot statistically determine whether there is a difference between annual and quarterly disclosures in regression of three-month return on *Sentiment* measure. However, for the regression of our four similarity measures, we find a statistically significant negative relationship. This indicates, *ceteris paribus*, that the returns following annual disclosures are on average lower than return following the quarterly disclosures.

Explaining Changes in Reporting Behavior

Based on the main findings of the similarity measures we wish to investigate for a potential relationship between change in similarity and the sentiment. To explore the contribution of *Sentiment* as a mechanism or cause behind the change in the reporting behavior of the firms, we regress each of our similarity measures on the sentiment measure. The notion is that similarity relationship with the return to some degree might be explained by the change in sentiment. We therefore believed that change in word phrasing towards a negative sentiment could indicate more change between the documents and therefore lower subsequent returns. We chose to divide financial disclosures into two segments, quarterly and annual. This is done to control for differences between the disclosures, as annual disclosures often are more comprehensive and have a different structure than what typically is found in quarterly. **Table 6** and **Table 7** shows the results of cross-sectional OLS regression of document similarity scores on sentiment characteristic.

Results in **Table 6** suggests that an increase in the *Sentiment* score of quarterly disclosures is positively associated with an increase in similarity between the documents, as measured by *Sim_Jacard*, *Sim_simple*, and *Sim_Minedit*. Inverse interpretation of these results suggests that lower similarity across the documents can to a degree be attributed to the negative sentiment

(tone) of the documents. Specifically, an increase in the number of negatively classified words. The finding applies for *Sim_Jaccard*, *Sim_simple* and *Sim_Minedit* similarity, as they are statistically significant.

As we can see from the results in **Table 7** for annual disclosures, we find *Sentiment* to be statistically significant in relation with *Sim_Jaccard*, but with a negative sign of the coefficient. We note that the negative sign is conflicting with our finding in **Table 6** for the mechanism test in the quarterly disclosures. We also note a possible connection to the main results where the dummy variable for annual disclosures was found to be not statistically significant for the *Sentiment* regression. That the annual disclosures behave differently might be due to the different traits of the disclosures such as larger size or more stale information than what is contained in quarterly disclosures. Furthermore, there is also a notable difference between the size of the sample of annual and the sample of quarterly disclosures.

7. Discussion

The statistically significant findings for three of our similarity variables indicate that firms who make substantial changes to the structure or textual content of financial disclosures as compared to previous year are likely to experience lower returns in the following next three months after publication. Accordingly, we can assume that substantial changes in periodic financial disclosures carry an informational value associated with the future short-term performance of the stock. However, we must point out that these results hold true in a cross-sectional perspective and that this relation might not always hold for individual firms. In practice, a substantial change in financial disclosures of the firms can also be attributed to new opportunities, improvements, acquisitions, expansion of operations or other favorable news that management wishes to convey to company's outsiders. In general, one cannot expect that corporate financial disclosures will be perfectly static over time. Firms' conditions of operations are constantly changing following the dynamics of markets, affecting the performances, and thus affecting the form and content comprising the financial disclosures. One can argue whether the substantial changes in reporting practices of the firms are motivated by management's incentives to obfuscate the unfavorable results or performance outlooks, restricting the availability of this information to the corporate outsiders. Considering that financial disclosures are guarded by the strict set of reporting regulation, management may try to avoid sending profound signals about poor expected performances to the markets, hiding the

subtle information within the textual-content and structure of the disclosures. Since we do not directly test for the obfuscation or impression management, we can only assume that substantial deviations from the average change to corporate disclosures can signal problems ahead. Nevertheless, we observe the tendency that substantial deviation from previous reporting practices may be indicative of management's subtle need to disclose about critical issues or outlooks that may have negative implications on the firm's future performances. Based on the result of our research we believe that corporate agents are to a certain degree aware about what signals they might be sending through their reporting practices, and therefore try to maintain status Quo when business is going well. Furthermore, our results are supporting the initial assumption of the default behavior of the corporate agent suggested by Cohen et al.⁴⁰

While annual and quarterly reports share many traits, there are also some distinct features between them. Following the logic thinking when considering annual disclosures, the fact that they are generally more comprehensive should lead them to be more informative about the financial condition of the firm and prospects. Further, annual disclosures are assumed to be followed by a greater audience than the quarterly, thus exposing the disclosures to more scrutiny. In the Norwegian context, the annual disclosures are considered as the summary of the fiscal year performances. Leading to the conclusion that the informational content of this type of reporting may be of limited value to corporate outsiders. Furthermore, Ernst & Young found in their annual practice survey for 2011, that 45% (2010:55%) of Norwegian listed companies used the account from the fourth quarter disclosures in their audited annual financial statements.⁴¹ Thus, further supporting the assumption that information presented in annual disclosures is already known to the market through other sources. On the other hand, the comprehensive nature of annual disclosures, the average annual disclosure are eight times more extensive in terms of textual content compared to quarterly, can to a degree hamper corporate outsiders from recognizing the true informative value of this type of disclosure.

Further, we find that the Sentiment variable has a significant and positive relationship with future three-month returns. This implies that an increase in the frequency of positive words or a decrease in negative words is associated with higher returns. The finding supports the initial results of Feldman et al.⁴², who found that change in tone conveyed through MD&A narratives

⁴⁰ (Cohen, Malloy, & Nguyen, 2016)

⁴¹ (Ernst & Young, 2012)

⁴² (Feldman, Govindaraj, Livnat, & Segal, 2010)

is positively associated with short-term returns. Due to the nature of our method of research, we are unable to say whether the tone change is confined to some specific section in financial disclosure. However, our findings suggest that firms with an overall negative sentiment (tone) conveyed through their financial disclosures perform worse. Although the rational explanation behind this finding may be not that surprising, bad news for the firm today results in less favorable performances in the future. We find it intriguing that we were able to measure this relationship with lagged returns based on publicly available information for the Norwegian listed companies.

Additionally, we tested a hypothesized potential mechanism behind the change to textual content and structure of corporate disclosures. The finding suggested that a change in sentiment towards a generally negative tone in quarterly disclosures could be associated with increasing change to textual-content and structure of the disclosures. Following our previous finding, such increase will likely indicate lower short-term excess return in the following three months. Based on this, we find it interesting that in a cross-sectional setting there is a positive association between the changes in reporting practices of the firms and the tone conveyed in disclosures. To what degree one is driving the other is a bit unclear. However, the relationship further confirms that substantial changes to the language used in disclosures are likely to be associated with increased pessimism and undesirable outlooks for the firm.

Goodness-of-fit of the main regressions describes how much of the variation is explained by the fitted regression line and is denoted as R-squared in **Table 5**. For our main regression, models with statistically significant variables of interest the R-squared ranges between .0581 and .0601. Comparing the overall regression fit with the models used in the similarity study by Cohen et al.⁴³ and the sentiment study by Feng Li⁴⁴, we find that the model fit is reasonably close to the results reported by other studies. Leading us to a conclusion that although there are some region-specific notable differences in financial reporting environment between U.S. and Norwegian listed companies, the relations found by previous research in the field also tends to apply in the Norwegian context.

⁴³ (Cohen, Malloy, & Nguyen, 2016)

⁴⁴ (Li, Do Stock Market Investors Understand the Risk Sentiment of Corporate Annual Reports?, 2006)

7.1 Assessment

Assessing our thesis, we find both strengths and weaknesses. Our thesis is based on similarity measures anchored to previous empirical research in the field. This gives us a reference point to build our research and enables us to explore it in a new context. Both the implication of change in similarity and variation in sentiment has been applied towards a new market to explain or predict the returns. However, our sample size is lower than other similar international studies. This is primarily due to the limitation in investigating a smaller market and the adversity in the data collection. Additionally, there are different market regulations affecting the content and the frequency of the disclosures. These differences make it inconvenient to directly compare our measurements with other studies, but the findings can still give an indication of the overall shared traits. Furthermore, our research method does not include all the control factors found in some of the literature, of the more commonly used, we find accounting for accruals and standardized unexpected earnings. While it could indeed be beneficial to include these additional control factors, we had to consider the feasibility of completing the thesis within the timeframe. Controlling for endogenous performance changes would be helpful in isolating the impact of the corporate disclosures changes.

For further research, we have identified three key areas we believe can be of interest.

First, the sentiment wordlist could be improved in multiple ways. By classifying more words, researchers can increase the precision of how much of the sentiment in the text is captured. Depending on the technique used to measure semantics one could potentially include concept level rather than word level to refine the measurements further. Additionally, one should consider the possibility of developing a customized wordlist for the Norwegian language that would enable research on the native Norwegian disclosures. This development could give insight whether there is any information loss during translation from native Norwegian to the English language. There would also be the benefit of increasing the possible sample size. A larger sample is always advantageous as it provides more data and therefore can help to reduce the margin of error. Secondly, considering that the management and discussion part of the reports is usually found to be the most concentrated area of both freedom and information richness about the firm's prospects. Researchers could focus the analysis on this specific section or any other narrative sections. The benefit could be better measurements and prediction, as "noise" from other sections would be disregarded. Thirdly, with the recent change in reporting requirements that only oblige firms to disclose on a half-year and annual

basis, one might be interested if this changes the informational value of the disclosures, or otherwise affect our findings. A longer time horizon and additional control factors could improve the measurements and model. Moreover, give insight if our findings are consistent over time and under the new regulations.

7.2 Summary

The thesis explores whether changes in tone, structure, and textual content of corporate financial disclosures published by Norwegian listed companies carry any information value that could have potential implications on subsequent short-term returns. Results of our research suggest that after controlling for known stock predictors and other relevant variables, substantial change to the textual content of corporate financial disclosures for Norwegian listed companies is associated with lower subsequent short-term returns. Furthermore, the change of word phrasing in textual content towards a negatively loaded sentiment (tone) is also associated with lower subsequent short-term returns. Additionally, we find that the increase in changes to textual content and structure of the quarterly corporate disclosures is positively associated with an increase in negative sentiment. Further confirming that substantial deviation in reporting practices of the firms are associated with an expected decrease in future performances.

8. References

- Alexander, D., & Schwencke, H. R. (2003, September). Accounting change in Norway. *European Accounting Review*, pp. 549-566.
- Bartlett, S. A., & Chandler, R. A. (1997, September). The corporate report and the private shareholder: Lee and Tweedie twenty years on. *British Accounting Review*(Vol.29(3)), pp. 245-261.
- Brown, S. V., & Tucker, J. W. (2011, May). Large-Sample Evidence on Firms' Year-over-Year MD&A Modification. *Journal of Accounting Research*(Vol.49(2)), pp. 309-346.
- Cohen, L., Malloy, C., & Nguyen, Q. (2016). *SSRN eLibrary*. Retrieved 2018, from Lazy Prices by Lauren Cohen, Christopher J. Malloy, Quoc Nguyen ::SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1658471
- Cole, C. J., & Jones, C. L. (2005). Managements Discussion and Analysis: A Review and Implication for Future Research. *Journal of Accounting Literature*(Vol.24), pp. 135-174.
- David Hirshleifer, S. H. (2003, December). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*(Vol.36(1-3)), pp. 337-386.
- Ernst & Young. (2012). IFRS - håndboken 2012. Ernst & Young.
- Exchanges, W. F. (2017). *WFE Annual Statistics Guide 2016*. Retrieved 2018, from Annual Statistics: <http://www.world-exchanges.org/home/index.php/statistics/annual-statistics>
- Feldman, R., Govindaraj, S., Livnat, J., & Segal, B. (2010). Management's tone change, post earnings announcement drift and accruals. *Review of Accounting Studies*(Vol.15(4)), pp. 915-953. Retrieved from Managements Tone Change, Post Earnings Announcement drift and Accruals: EBSCOhost: <http://web.a.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=1&sid=d55477b1-8193-45d8-a3c9-7475069f1c52%40sessionmgr4010>
- Finansdepartementet. (2004). *Lovdata*. Retrieved from Delvis ikrafttredelse av lov 10. desember 2004 nr. 81 om endringer i lov 17. juli 1998 nr. 56 om årsregnskap m.v. (regnskapsloven) og enkelte andre lover (gjennomføring av EØS-regler om anvendelse av internasjonale regnskapsstandarder m.m.): <https://lovdata.no/dokument/LTI/forskrift/2004-12-10-1610>
- Finansdepartementet. (2007). *Lovdata*. Retrieved from Lov om verdipapirhandel (Verdipapirhandelloven)- Lovdata: <https://lovdata.no/dokument/NL/lov/2007-06-29-75>
- Finansdepartementet. (2007). *Lovdata*. Retrieved from Verdipapirforskriften - Lovdata Pro: <https://lovdata.no/pro/#document/SF/forskrift/2007-06-29-876?searchResultContext=2776>
- Finansdepartementet. (2010). *Lovdata*. Retrieved 2018, from Lov om verdipapirhandel (verdipapirhandelloven) Del 2. Generelle bestemmelser Kapittel 5. Løpende og periodisk informasjonsplikt, offentliggjøring mv.: https://lovdata.no/dokument/NL/lov/2007-06-29-75/KAPITTEL_2-3#KAPITTEL_2-3
- Finansdepartementet. (2018). *Lovdata*. Retrieved from Lov om verdipapirhandel (verdipapirhandelloven): https://lovdata.no/dokument/NL/lov/2007-06-29-75/*#*
- IASPlus*. (1999). Retrieved 2018, from IAS 34 — Interim Financial Reporting: <https://www.iasplus.com/en/standards/ias/ias34>
- IFRS Foundation. (2017). *IFRS*. Retrieved from IFRS - Why global standards: <https://www.ifrs.org/use-around-the-world/why-global-accounting-standards/>

- Jones, M. J., & Shoemaker, P. A. (1994). Accounting narratives: A review of empirical studies of content and readability. *Journal of Accounting Literature*(Vol.13), pp. 142-184.
- Li, F. (2006, April). Do Stock Market Investors Understand the Risk Sentiment of Corporate Annual Reports?
- Li, F. (2008, August). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics*(Vol.45(2-3)), pp. 221-247.
- McDonald, B. (2015, March). *University of Notre Dame*. Retrieved December 2017, from Bill McDonald's Word List Page: https://www3.nd.edu/~mcdonald/Word_Lists.html
- McDonald, B. (2018, May 1). Private e-mail correspondance.
- Merkel-Davies, D. M., & Brennan, N. M. (2007). Discretionary disclosure strategies in corporate narratives: incremental information or impression management? *Journal of Accounting Literature*(Vol.27), pp. 116-196.
- MSCI. (2018, May). Retrieved from GICS - MSCI: <https://www.msci.com/gics>
- Nelson, K. K. (2007, August). Litigation Risk and Voluntary Disclosure: The use of Meaningful Cautionary Language.
- Norsk RegnskapsStiftelse*. (2011). Retrieved from NRS 11 Delårsrapportering (OPPHEVET): <http://www.regnskapsstiftelsen.no/regnskap/regnskapsstandarder/nrs-11-delarsrapportering-opphevet/>
- Oslo Børs*. (2017, May). Retrieved March 29, 2018, from 2017 Facts and figures May 2017: https://www.oslobors.no/ob_eng/Oslo-Boers/Statistics/Facts-and-figures/2017-Facts-and-figures-May-2017
- Oslo Børs*. (2018). Retrieved 2018, from Comparisson between Oslo børs, Oslo axess and Merkur Markets: https://www.oslobors.no/ob_eng/Oslo-Boers/Listing/Shares-equity-certificates-and-rights-to-shares/Comparison-between-Oslo-Boers-Oslo-Axess-and-Merkur-Market
- Python Library Reference*. (2006, October 18). Retrieved from 4.4.1 SequenceMatcher Objects: <https://docs.python.org/2.4/lib/sequence-matcher.html>
- Randi Næs, J. A. (2008, November). Hvilke faktorer driver kursutviklingen på Oslo Børs? *Norsk Økonomisk Tidsskrift*(123), pp. 36-81.
- Regjeringen*. (2017). Retrieved from Ofte stille spørsmål - Regjeringen.no: <https://www.regjeringen.no/no/tema/europapolitikk/fakta-115259/ofte-stilte-sporsmal/id613868/>
- Rogers, R. K., & Grant, j. (1997). Content analysis of information cited in reports of sell-side financial analysts. *Journal of Financial Statement Analysis*, pp. 17-30.
- SKIPSREVVYEN*. (2015, May). Retrieved from Frontline 2012-aksjonærene vinnerne i fusjonen: <https://www.skipsrevyen.no/article/frontline-2012-aksjonaerene-vinnerne-i-fusjonen/>
- Stortinget*. (1998). (Finanskomiteen, Producer) Retrieved from Instilling fra finanskomiteen om lov om årsregnskap m.v. (regnskapsloven): <https://www.stortinget.no/no/Saker-og-publikasjoner/Publikasjoner/Innstillinger/Odelstinget/1997-1998/Inno-199798-061/?!vl=0>
- The European Parliament and the the council og the EU. (2002, May 27). *IASPlus*. Retrieved from Regulation of the European Parliament and of the Council on the application of international accounting standards: <https://www.iasplus.com/en/binary/resource/euiasreg.pdf>
- Thompson Reuters Eikon*. (2018, April 28). Retrieved from .OSEAX OV, Constituents, Market cap, GICS sector name: <https://emeal.apps.cp.thomsonreuters.com/web/Apps/Index?s=.OSEAX&st=RIC&app=true#/Apps/IndexReports>

- Woolridge, J. M. (2013). *Introductory Econometrics: A Modern Approach* (5th edition ed.). South-Western, Cengage Learning.
- Ødegaard, B. A. (2018, February). *Asset pricing data at OSE*. Retrieved from http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html