BI

WISEflow
Europe/Oslo(CEST)
30 Jun 2022

Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	16-01-2022 09:00	**Termin:**	202210
Sluttdato:	01-07-2022 12:00	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202210||10936||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

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Informasjon fra deltaker

Tittel *:	CEO Characteristics and Corporate Leverage A Norwegian Perspective
Navn på veileder *:	Siv J. Staubo

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	52
Andre medlemmer i gruppen:	

BI Norwegian Business School
Study Program: MSc Finance
Supervisor: Siv J. Staubo
Delivery date: 29.06.2022

CEO Characteristics and Corporate Leverage

A Norwegian Perspective

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Abstract

We study the relationship between CEO Characteristics and corporate leverage in Norwegian listed companies using an unbalanced panel of 303 firms from 2000 to 2017. To study the relationship, fixed effects regressions and gradient tree boosting in XGBoost are used. We ask, "Does CEO Characteristics affect financial leverage?". We were not able to confirm that CEO characteristics are causing corporate leverage, but CEO Salary does have a correlation across models. The lack of a strong effect found in our thesis is a healthy sign in terms of corporate governance in listed Norwegian companies. We also confirm that commonly accepted determinants of capital structure do predict leverage ratios on the Norwegian stock exchange as found in the literature.

Keywords: Behavioral Finance, Capital Structure, CEO characteristics, Corporate Finance, Corporate Governance, Corporate Leverage, Norwegian Stock Market

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1 Introduction

In our study we investigate the connection between CEO characteristics and corporate leverage in companies listed on the Norwegian stock market. CEO characteristics are descriptive characteristics about an individual CEO such as tenure, salary, stock ownership, age or gender. The corporate leverage ratio is the proportion of the company, which is financed using debt, or in other words the composition of equity and debt in the company. Too little or too much can affect the company's valuation and/or risk profile.

The existing literature has typically focused on firm, market, and industry characteristics to explain different capital structures in firms. We confirm that these capital structure determinants are important, but our study tries to see if CEO characteristics have an effect on the leverage ratio of Norwegian listed companies. As the CEO effectively could control the day-to-day operations of the company, we can assume that he could affect the amount of debt (or financial risk) the company takes on. In companies with good corporate governance, we expect that the CEO does not have a lot of personal impact on the leverage ratio. If CEO characteristics are found to have a significant and strong effect, the implications would be that the CEO has a personal impact on leverage decisions. This would indicate that the "chain of command", from owners to board to CEO, is not followed. Implicitly, poor corporate governance.

Our main question is: Does CEO Characteristics affect financial leverage? We subdivide this main question into five sub questions. The questions are:

1. How does tenure affect corporate leverage?
2. Is the CEO living the quiet life? (CEO Salary and Leverage)
3. How does the ownership stake of the CEO affect the leverage ratio?
4. How does CEOs age impact corporate leverage?
5. How does gender impact the corporate leverage?

Knowledge about these questions could be used to help the owners and board to improve corporate governance such that the interest of the owners and managers are aligned.

There were two important papers that inspired our thesis. “Upper Echelons: The Organization as a Reflection of its Top Managers” by Donald C. Hambrick and P. Mason (1984), which states that *“organizational outcomes are partially predicted by managerial background characteristics” (p. 193)*. This paper led to the development of a branch in behavioral finance called *“Behavioral Consistency Theory”*. The main inspiration for our thesis was Cronqvist, Makhija and Yonker’s (2012) study *“Behavioral consistency in corporate finance: CEO personal and corporate leverage”*. They studied whether the CEOs personal leverage could explain the corporate leverage of the company. The conclusion was that the personal leverage ratio of the CEO is consistent with the corporate leverage in the company.

BI’s CCGR (Centre for Corporate Governance Research) database provides us a comprehensive dataset for the period 2000-2017 with every listed company on the Norwegian stock market. Our dataset includes accounting variables and different CEO characteristics all provided as tabular data. We ran several fixed industry panel regressions with corporate leverage as the dependent variable, and CEO characteristics and control variables as independent variables. Also, we use boosted regression trees implemented in the package XGBoost in R as a robustness check and confirmatory analysis. Our results indicate that listed companies in Norway have good corporate governance, and this is due to the lack of a strong CEO effect on financial leverage decisions. We do however find a negative relation between CEO Salary and leverage ratio.

2 Literature Review and theory

In the literature review we first introduce common capital structure theories, followed by known capital structure determinants. We then introduce CEO Characteristic theories, followed by determinants of CEO Characteristics.

2.1 Capital structure theories

2.1.1 Miller-Modigliani theorems and capital structure irrelevance

Miller and Modigliani (1958) started what we today see as the modern capital structure research. MM´s proposition 1 is saying that financing decisions is irrelevant for the fundamental value of a firm in perfect capital markets. The irrelevance of financing generalizes to any security if the following five assumptions hold (Myers, 2001). 1) Perfect capital markets; a market without transaction costs when issuing and trading securities, no bankruptcy costs, no taxes, no monitoring costs. 2) All market participants have equal access to capital markets. 3) All information is public information. It is freely available to all market participants, and they agree on the influence it has on the future of firms and securities. 4) Only wealth counts. The characteristics of the investment opportunities available to investors is not affected by the capital choice of a firm (aside from effects on security holder wealth). 5) Investment strategies is given and independent of a firms' capital structure (Fama, 1978).

It is possible to see that relaxing the assumptions would get us closer to the real world, and then we could investigate the real impact capital structure has on the fundamental value of firms. The theories presented in the following differ in terms of their focus on taxes, asymmetric information, and agency costs, they show that financing decisions does matter (Myers, 2001).

2.1.2 Tradeoff theory

Kraus and Litzenberger (1973) theorized the existence of an optimal financial leverage which maximizes firm value, also known as a target capital structure. The theory says that a firm will borrow up to the point where the marginal value of tax shield is just offset by the marginal cost of financial distress (Myers, 2001)[1].

If the probability of financial distress is low for a value-maximizing firm, then according to the tradeoff theory we should see that the full amount of the tax shield is used. It is however many examples of highly profitable firms with good credit rating and conservative leverage ratios (Graham, 2000; Myers, 2001). Kayhan and Titman (2007) is suggesting that the relation between leverage ratio and firm value could be relatively weak, such that the concept of a target leverage ratio is less of importance. Graham and Harvey (2001) found in their study that 44% of CFOs had a target debt to equity ratio, ranging from somewhat tight to very strict target. 37% reported a flexible target, and 19% reported no target. They also identified the most important debt policy factors to be *financial flexibility*[2] and *credit rating*. Other factors identified as important in their study was *earnings and cash flow volatility*, *insufficient internal funds*, *level of interest rates*, and *interest tax savings*.

2.1.3 Pecking order theory

From another perspective, if we relax assumption 3 (all information is considered public information) we could look at capital structure in the way Myers and Majluf (1984) does in their paper on the pecking order theory. When a company is investing in projects, it needs to decide whether it would like to raise external or internal capital to fund it. Asymmetric information affects this choice, managers know more about their own firms than any outsider and creates a gap and an uncertainty in the value of the firm. A pecking order is therefore present, where internal funds are used first, then debt and lastly new equity issuance. Equity issuance will only be chosen if the company runs out of debt capacity, or they consider the company as overpriced. In this theory, with two different types of equity, one as the first choice of capital and one as the last choice, we do not observe a target debt-to-equity ratio for different firms. The debt

[1] *"Financial distress refers to the costs of bankruptcy or reorganization, and also to the agency costs that arise when the firm's creditworthiness is in doubt"* (Myers, 2001, p. 89).

[2] Financial flexibility refers to the survey. The participants were asked to grade the following regarding financial flexibility. *«We restrict debt, so we have enough internal funds available to pursue new projects when they come along»*. Credit Rating refers to having the leverage at a level which gives high credit rating.

ratio is reflected in the overall requirements for external finance for the specific firm (Myers and Allen, 2019, p. 479-451). Frank and Goyal (2009) argue that the different sources of financing have different types of adverse selection issues (asymmetric information). As internal financing has no “counter party”, there is no adverse selection problem here. On the other hand, debt and new equity are much more prone to this issue. The riskier the capital is, the more present adverse selection problems are.

2.1.4 Market Timing Theory

Introduced by Myers in 1984[3] the market timing theory predicts that managers choose debt or equity issuance based on which of the two markets look more “favorable”. It is also argued that if conditions are particularly favorable the managers could raise debt or equity even though they have no need for the funds at the time.

2.1.5 Agency theory

Adam Smith in his 1776 Wealth of Nations writes that *“Managers of other people’s money rarely watch over it with the same anxious vigilance with which they watch over their own”*. Jensen and Meckling (1976), and other scholars view the firm as a set of contracts between factors of production. Each of the factors have its own self-interest, but typically fulfill their part of the contract. The manager is presumed as the agent, he would therefore act in his own interest by for example higher salary, empire building, aligning assets and operations to his skills. Efforts from the shareholders to align incentives such as monitoring and control, managerial ownership, compensation schemes etc. could be introduced to limit value transfers. As these efforts comes at a cost and therefore give smaller returns, we would not be able to monitor/control/align perfectly away the effect of the agency problem (Myers, 2001).

Discussion outlined above brings us to the free cash flow (FCF) theory by Jensen (1986). If all positive NPV projects have been granted funds, there could be FCF left to invest in projects that destroy value. Through empirical research it is found that the manager has incentives to invest too much. For example, Bebchuk and Grinstein (2007)

[3] Not to be confused with Myers and Majluf also from 1984.

found *"a positive and economically meaningful correlation between CEO compensation and the CEO's past decisions to increase firm size" (p. 1)*. With an optimal debt level, it is possible to limit the amount of free cash flow available to management such that it equals optimal amount needed to invest in all positive NPV projects. Myers (2001) points out that taking a company on a diet in the form of debt could add significant value, but it is clear that this would not always be done voluntarily by the management. This could assist the tradeoff theory to explain why managers do not commit to debt ratios that fully take advantage of the tax shield (Myers, 2001).

2.2 Determinants of capital structure

To understand the relationship between CEO characteristics and corporate leverage, we first need to understand the determinants of capital structure. There has been some research on capital structure in the Norwegian markets done by PhD-graduates using the CCGR[4]-database (García de Olalla, 2014). Remners et al. (1974) did a study on large companies and debt ratio determinants in different countries, and Norway is one of them. Rajan and Zingales (1995) did a study on corporate leverage across the G-7 countries[5], and their findings suggest that leverage is similar for listed companies in the respective countries. This is valuable because much of the research conducted on corporate leverage has been on listed companies (excluding financial companies) with access to American or international capital markets. More financing choices are available for these companies, and they can change their capital structure at a relatively low cost.

Several authors have proposed different determinants for corporate leverage. These will mainly act as our control variables. As a measure of capital structure, several choices can be made. The choice is between D/E ratio or D/Value ratio. The two units say the same thing, but on different scales. Different scholars use purely book values, purely market values or combinations of both. Frank and Goyal (2009), uses TDM, i.e., total debt to market value of assets. Lemmon, Roberts and Zender (2008) use purely

[4] Centre for Corporate Governance Research. A BI Norwegian Business School database.
[5] United States, Japan, Germany, France, Italy, the United Kingdom, and Canada.

book values. Regarding our thesis we follow Zender et al (2008) and use book values of total debt to total assets.

$$Leverage\ Ratio = \frac{Book\ value\ of\ Total\ Debt}{Book\ value\ of\ Total\ Assets}$$

We have compiled a list of the most important determinants of the leverage ratio concerning our thesis and why we chose them:

2.2.1 Profitability

Rajan and Zingales (1995) found that profitability is negatively correlated with leverage and found it in many other scholars' works. Frank and Goyal (2009) empirically studied public American firms from 1950 to 2003 and found that more profitable companies tend to have less debt. This is in line with the pecking order theory. An opposing view presented by Frank and Goyal is that *''Profitable firms face lower expected costs of financial distress and find interest tax shields more valuable''* (2009, p.7). This is what they call the *tax and bankruptcy perspective*, and they hypothesize that profitable companies use more debt. This would be in line with the standard tradeoff theory. Free cash flow theory suggests that a diet in the form of debt would be more valuable for profitable firms since they are more likely to have a free cash flow problem. Frank and Goyal calculated profitability as the operating income before depreciation to assets. This considers the income that is available to all financial claimants after taxes is paid[6]. We use Return On Assets as our profitability measure:

$$Profitability = ROA = \frac{EBI}{Total\ Assets}$$

[6] Alternatively, using return on equity would only take into consideration the equity holders claim, and not the debt holders claim.

2.2.2 Firm size

Rajan and Zingales (1995) found that firm size is positively correlated with leverage. They found it to be one of the most consistent leverage determinants when reviewing other scholars work. Frank and Goyal (2009) found that companies with more assets tend to have *"relatively more debt*[7]*"* (p. 7). The rationale is that bigger companies are more diversified and have lower default risk which is consistent with the tradeoff theory.

The market timing theory would also support this claim, such that bigger companies, which are profitable and have assets in place have more leverage, when debt financing is cheap, i.e., when the central bank interest rate is low. Another view is that large firms are older and better known and can retain earnings. This would be aligned with the pecking order theory (Frank and Goyal, 2009). Frank and Goyal used the natural logarithm of assets, deflated using the GDP deflator. Regarding our thesis, we choose the natural logarithm of book total assets as our size measure, after adjusting for inflation.

$$Size = LN(Total\ Assets)$$

2.2.3 Tangibility

Rajan and Zingales (1995) found that tangibility of assets is positively correlated with leverage. They considered tangibility as one of the factors that showed up most consistently in other scholar's papers. Frank and Goyal (2009, p.10) found that companies with *"more tangible assets tend to have higher leverage".* They compute tangibility as the ratio between net property, plant, and equipment to assets. The idea is that companies with more tangible assets are easier to value, and effectively "collateralize" the assets which eases up leverage. This is consistent with the tradeoff theory.

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[7] For book values of leverage, as opposed to market value of leverage, they however found that firm size, market to book-ratio and inflation effects are not reliable.

In the pecking order perspective, *“leverage ratios should be lower for firms with higher tangibility”(2009, p. 9)*, and Frank and Goyal argue that if there is little doubt of the assets value, equity issuances should be less costly, resulting in lower leverage. However, if we have an adverse selection problem, with more uncertainty about the assets value, the opposite could be true. We use a similar measure to that of Frank and Goyal, and calculate:

$$Tangibility = \frac{Book\ Tangible\ Assets}{Book\ Total\ Assets}$$

2.2.4 Firm Age

Brav (2009) found that leverage decreases as age increases. He writes that “*Firm age may also effect the debt-equity composition because as firms age, they become known to the market, which can expand their access to capital”*(p. 280). Frank and Goyal (2009) write similar arguments to that of firm size. We quote: *“The pecking order theory is usually interpreted as predicting an inverse relation between leverage and firm size and between leverage and firm age. Large firms are better known, as they have been around longer. In addition, older firms have had an opportunity to retain earnings”(p. 8)*. Firm age is easy to measure precisely, and we measure it in years.

2.2.5 Dividend payments

Frank and Goyal (2009) conclude that dividend paying firms, tend to have lower leverage. They, however, conclude that the use of a dividend dummy is inconclusive in the literature/among other scholars. We include a dummy as control variable if the company is paying dividends or not.

2.2.6 Other determinants not used

Rajan and Zingales (1995) found that the market-to-book ratio is positively correlated with leverage. They view the market-to-book ratio as a proxy for investment opportunities and considered it one of the most observed determinants of capital structure when reviewing other academics work. They also point out non-debt tax shields (positive)[8], volatility (negative), probability of bankruptcy (negative), and uniqueness of the product (negative) as important determinants of capital structure.

Frank and Goyal (2009) write that *"the market to book assets ratio is a commonly used proxy for growth opportunities"* (p.9) and also "*the most reliable*" (p.9) according to Adam and Goyal (2008). We don't have stock data for every company in our data set. As an alternative to the market to book assets ratio, we could use sales growth as a proxy for growth the following year, as Brav (2009) proposes. We calculated it as

$$Growth\ Opportunities = \frac{Sales_{t+1} - Sales_t}{Sales_t}$$

We, however, concluded by looking at the data, that it is too non-gaussian to be used for our regression. Also, Brav uses it purely for privately held companies which are outside of our study.

Hovakimian, Opler and Titman (2001) show that companies actively adjust their capital structure towards the industry average[9]. Frank and Goyal (2009) found that *"firms in industries in which the leverage is high, tend to have high leverage"*(p.3). Other researchers argue that Industry *Median Leverage* is a proxy for the firm's target capital structure, i.e., the tradeoff theory. Frank and Goyal (2009) argue that *"under a pure pecking order perspective, the industry should only matter to the extent that it serves as a proxy for the firm's financing deficit – a rather indirect link"* (p.9). They also argue that under the market timing theory perspective, "*the industry should matter only if valuations are correlated across firms in an industry"* (p.9). Lemmon, Roberts and Zender (2008) describe industry median leverage as *"the single most influential observable determinant of book leverage*" (p.1576). We conclude that it is artificial to use a variable calculated from the leverage ratio in order to explain the leverage ratio, and do not use the industry median leverage as a control variable.

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[8] Parentheses inform correlation to leverage ratio.
[9] As opposed to industry median

2.3 CEO characteristics

By studying the relationship between CEO characteristics and corporate leverage we could say something about the company's capital structure. Hambrick and Mason (1984) proposed that the organization is a projection of its managers, i.e., the company's upper echelons. They found some evidence for a connection between the top managers' personal preferences and how the company is run. Cronqvist, Yonker and Makhija (2012) found a connection between the CEO's personal leverage and the corporate leverage of the company the CEO is leading. They found a positive robust relation between corporate and personal leverage in the cross-section and when they examined CEO turnover. Their findings contribute to the research supporting the fact that CEOs' behavior can explain some of the corporate financial behavior we see in the firms they manage. This paper is the main inspiration for our master thesis. We are not able to collect data about the CEOs' personal leverage, so we will instead use other observable CEO characteristics from the CCGR database to see if they could explain corporate leverage in the Norwegian stock market.

According to the literature review of Ishak (2020), the ongoing debate of the CEO's impact on firm performance, has shifted from if the CEO has an impact, towards what characteristics have the most impact. Quigley and Hambrick (2015) argue that the "CEO effect" has *"increased substantially over decades of the study"* (p.821). CEO characteristics research is according to Shen (2021) all derived from Upper Echelon Theory by Hambrick and Mason (1984). Shen also points out 4 distinct perspectives of CEO characteristics research: Management, strategy, finance and interdisciplinary.

2.3.1 Do managers really matter?

Bertrand and Schoar (2003) found evidence that the specific executive in charge of a US company systematically impacts the realization of all investment, financing, and other organizational strategy variables. They also found that older managers on average are more conservative when it comes to financing. They used a fixed effects model to find CEOs, CFOs, and other executives' impact on the organizational strategy variables, but the managers must have worked for more than one firm. Executives that have an MBA are also found to choose more aggressive business strategies.

Frank and Goyal (2007) found evidence that the compensation structure for the CEOs affects the leverage choice for the firm. If the pay-for-performance is higher then their firm tends to have lower leverage. They are further able to document slight effects from a variety of characteristics, having an MBA, tenure, and educational background, which has statistical significance. It does, however, only count for a small amount of the variation in leverage or leverage adjustments. They found that CFOs matter more than CEOs when it comes to leverage choices.

Malmendier, Tate, and Yan (2011) found that measurable managerial characteristics have significant explanatory power for corporate financing decisions. They used a fixed-effects methodology where they compared CEOs with different traits operating the same firm. There are three main findings in their study: 1) When a manager believes that their firm is undervalued then they tend to view external financing as overpriced. They consequently use less external finance due to their overconfidence. 2) CEOs with childhood during the Great Depression are averse to debt and would mostly use internal financing. 3) CEOs with experience from the military use more aggressive corporate policies, including heightened leverage.

2.4 CEO Characteristics variables (CEO determinants of leverage)

Our data contains five variables regarding different CEO characteristics. Here is the literature explaining our choice of variables:

2.4.1 CEO Tenure

Malmendier, Tate and Yan (2011) found that overconfident managers have longer tenure, and at the same time they found that overconfident managers are less likely to use external financing. In other words, an indirect link. Graham and Harvey (2001) found in their survey that CEOs that are either young or have short tenure are more likely to have a target capital structure. Frank and Goyal (2007) found that CEOs with higher tenure have less debt in the company. CEO tenue is reported in the CCGR database, and we use it without modifications.

2.4.2 CEO Salary/Compensation

Tosun (2016) found that firms "*appear to decrease leverage when CEOs are paid with more stock options"* (p.953). In other words, the CEOs are less likely to take financial risk when they have more stock options in the company. Tosun uses a difference in difference approach to see the effect on leverage from an increase in salary and/or options. Bertrand and Mullainathan (2003) found some evidence that managers enjoy *"the quiet life"*, and that the CEOs are not necessarily occupied by empire building. Empire building is typically linked to higher leverage ratios. Consequently, *the quiet life* is linked with a lower leverage ratio.

Our dataset includes the variable CEO Salary which includes the base salary of the CEO, plus any other benefit he or she might have received during the period. This could be stock options, bonuses or added pension benefits. We gather the CEOs salary from CCGR, adjust for inflation and currency differences in the dataset, and lastly taking the natural logarithm.

2.4.3 CEO Ownership

Cronqvist, Makhija and Yonker (2012) show that CEOs with higher equity ownership in the company they are running have lower personal leverage. This implies from the previous discussion that higher ownership suggests lower corporate leverage. The natural logarithm of the market value of equity ownership pr CEO is used in their study. Since we are not able to consistently collect market values, we create a dummy for equity ownership, 1 for ownership and 0 otherwise.

2.4.4 CEO Age

Malmendier, Tate and Yan (2011) found that managers born during the great depression are more averse to debt. CEOs born during the great depression happens to be categorized as "older", so they don't necessarily claim that future "old" CEOs are conservative as well, and the interpretation must be put on life experiences. Bertrand and Schoar (2003) found that "*older generations of managers, on average, are financially more conservative"*(p.1205), claiming that older CEOs are more likely to have a lower financial leverage. Cronqvist et al. (2012) found that older CEOs have less personal leverage, and this implies lower corporate leverage. We collect the CEOs age from the CCGR database.

2.4.5 CEO Gender

The CEO's gender is a variable we have in our item list from CCGR. There is very little to no research on the gender of the CEO and capital structure of the company. Garcia and Herrero (2021) show that companies with a higher percentage of females on the board, have lower corporate leverage, however not directly applicable. Frank and Goyal (2007) found that female CFOs are more likely to have a lower corporate leverage. They were not able to find significant results for the female CEOs. Croson and Gneezy (2009) reviews experimental evidence on preference differences between men and women. They found that women are generally more risk averse. Women are also more cautious in their investment decisions.

The organization Catalyst (Catalyst.org, 2022), measured that 6.4% (32 female managers of 500) are female on the S&P500 index. This is representative regarding this thesis, as 3.95% of CEOs are female over the sample period. If this is representative for the rest of the world, then attributing any statistical significance to gender, except being male, would be on a small sample.

3 Data and preliminary analysis

Our data has been collected from BI's Centre for Corporate Governance Research (CCGR, 2022)[10]. It contains listed Norwegian companies from 2000 to 2017 and is structured as an unbalanced panel. The annual average of companies is 131 companies. CEO salary is systematically not reported for 2016 and has missing values randomly placed in other years. We predict the missing 653 salary values using XGBoost and the method is described in chapter 4.5 [11]. We have excluded the financial sector[12] from our

[10] The CCGR database contains accounting data for all companies in Norway, but also non-accounting corporate governance variables such as ownership structure, different family office variables, and CEO characteristics.

[11] We also studied the effect of leaving the observations out of the sample. It yielded similar results as predicting the missing values.

[12] Industry Sector Code 6

data as this is a sector different of the others because of higher leverage in general. The debt in the balance sheet also can't be compared directly to that of non-financial firms like Rajan and Zingales (1995) argues. In chapter 3.1 we introduce the key decisions regarding the CCGR dataset. Chapter 3.2 presents variable definitions. Chapter 3.3 presents descriptive stats, histograms, and other information about our main variables.

3.1 Decisions regarding the CCGR dataset

3.1.1 Main concerns about the dataset

We have three concerns regarding our dataset. First, our main concern was whether to use non-consolidated or consolidated accounting data. The reason was that some listed companies are not structured as a group[13]. Consequently, by only using companies which are not organized in the CCGR database (or at least reported) as a group will exclude about 30% of the dataset, leaving out many otherwise acceptable observations. To deal with this issue, we chose that accounting data was taken from the consolidated statements if the consolidated item was present. Second, in the dataset, firms did not usually report CEO salary in the consolidated statements. We therefore choose to not use CEO salary from the consolidated statements if it is present in the parent statement. If salary was present in both, they were often equal, or very similar. Third, as with all accounting data, this dataset could also suffer under measurement errors and differences in reporting. We explain how we try to mitigate some of these errors in the following chapters[14].

3.1.2 Currency, inflation, fiscal year, and reporting challenges

Although not very common in our dataset, differences in currencies do occur. Our data contains mostly NOK, but some companies report in EUR or USD. We will mostly look at ratios that eliminates this issue. We convert "monetary" items into NOK and adjust for inflation. *Norges Bank* provides the pr. annum 31.12 exchange rate for both Euro and USD, as well as the consumer price index, which we calculate the annual inflation from.

[13] We translate "Group» from the Norwegian equivalent of «Konsern».
[14] Also, we mention common endogeneity issues in chapter 4.6.

The most common is to report the fiscal year in the range from 01. January to 31.12 December each year. For simplicity we have assumed the fiscal year is equal for all companies, i.e., the standard period. This simplifies challenges to calculating the inflation and currency differences.

Since our sample contains only listed companies, we are mostly looking at consolidated statements. IFRS is mandatory in consolidated statements, but subsidiaries are allowed to use either Simplified IFRS or GRS (Regnskapsloven, 2022). It is still a recommendation in the legislation that for simplicity, subsidiaries use IFRS as they are required to in the consolidated statements. Adjusting for different accounting practices throughout the period 2000 to 2017 is also a clear challenge we are not able to control.

3.1.3 Logarithmic values

We take the natural logarithm of accounting items used in our regressions to correct for heteroskedasticity, help non-Gaussian data become more normally distributed and help make the non-linear, multiplicative relationship between variables into a linear and additive one. This approach is what Chris Brooks describes in his 2019 "Introductory Econometrics for Finance". This is applied for book total assets (Size factor) and CEO salary.

3.1.4 Industry sector

We were able to extract NACE codes and use the CCGR item list recipe to translate that into an industry sector code ranging from 1 to 9. The industry sector list can be found in chapter 8.1 Appendix. We had to adjust some values after 2009 to fit into the industry sector code system, as the NACE-standard changed then. There were only minor corrections made. Companies which had multiple sector-codes was categorized into sector 9 according to the CCGR-recipe. This did not include companies which had a single NACE code plus either 70.000 or 70.100 (main office). We wanted to avoid categorizing these as being multisector, because in our view, being a "main office" is not really a different sector, just the administrative hub of the company. For reminding, industry sector code 6, financials, was classified, then removed from the sample.

3.1.5 Excluded variables

Even though the industry median leverage is according to several scholars, a very strong predictor of leverage we chose to exclude it. We argue that it creates artificial results by using the companies own leverage to predict other companies leverage.

The central bank rate is equal for all companies. We argue that this is not a good predictor of the leverage of an individual company. We still include it for the gradient boosting/part two of our methodology to see the central banks rate "importance". Regarding the market value of equity for the CEO's ownership stake, we were not able to consistently find the market value of the sample companies, and the book value would also be a poor proxy for the market value. Sales growth included was too non-gaussian and was therefore not included in our regressions. Several papers argue for the use of the number of employees as a proxy for company size. It had too many missing or false values such that we were not able to make use of it. We therefore chose to exclude the number of employees as a size proxy.

3.2 Variable definitions

Our variables are grouped into 4 and are all measured at the 31.12 each year:

The first group includes the dependent variable, *Leverage Ratio,* computed as the ratio of book value of debt to book value of total assets. Winsorized at 1% lower level and 99.5% upper level.

The second group consists of the control variables. *Profitability*, *Size*, *Tangibility*, *Firm Age* and *Dividend.* Profitability is measured by return on assets (ROA). ROA is calculated as after-tax earnings before interest (EBI) divided by book total assets and is winsorized at 1% lower level and 99.5% upper level. Size is the natural logarithm of book total assets and is winsorized at 1% lower level and 99.5% upper level. Tangibility is the ratio of the book value of tangible assets to book value of total assets and is winsorized at 1% lower level and 99.5% upper level. Firm Age is the age of the company measured in years. Dividend is a dummy equal to 1 if the company paid dividends that year, and 0 otherwise.

The third group consists of the CEO characteristics variables, *CEO Tenure, CEO Salary, CEO Ownership, CEO Age* and *CEO Gender*. CEO Tenure is the CEO's time in the current position as CEO. CEO salary is the natural logarithm of the sum of the CEO's base salary, bonuses, options and any other compensation received. CEO ownership is a dummy equal to 1 if the CEO has ownership in the company, and 0 if not. CEO Age is the CEO's age measured in years. CEO Gender is a dummy equal to 1 if the CEO is male, and 0 if female.

The fourth group is the company and CEO classifiers. Industry Sector is the industry classifier ranging from 1-9 [15]. It is from this variable we have constructed the dummy-variables for each of the 8 sectors[16].

3.3 Exploratory data analysis (EDA)

3.3.1 Descriptive stats, histograms, and correlation matrix of variables

Continued next page

[15] Excluding financials firms, code 6.

[16] We remove the first dummy to avoid dummy variable trap while we have an intercept in our regression models (Brooks, 2019, p.451).

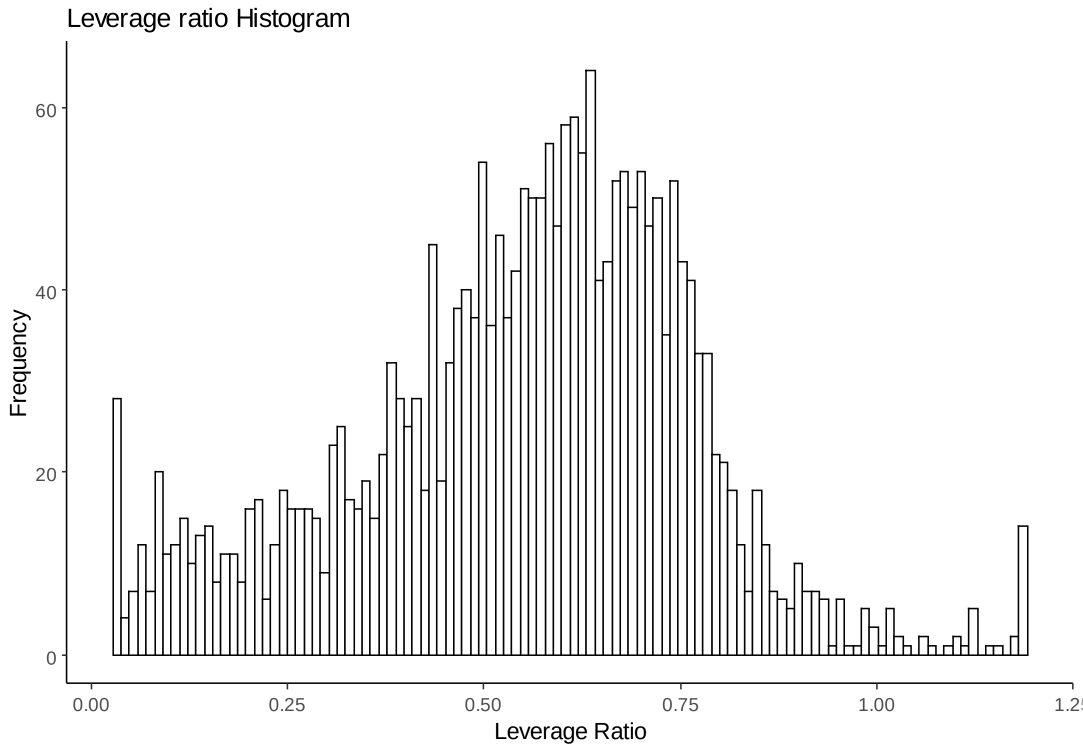
Table 1: Descriptive statistics								
The table presents descriptive statistics for the panel data, from 2000 to 2017. The data is unbalanced. In total there are 303 unique companies in the sample. The financial sector is excluded. Leverage ratio is the book total debt to book total value of the company. Profitability is measured as Return on Assets. Size is the natural logarithm of book total assets. Tangibility is the book value of tangible assets divided by book total assets. Firm age is the age of the company measured in years. Dividend is a dummy variable which equals 1 if the company pays dividends and 0 otherwise. CEO tenure is the time measured in years which the CEO has held the current position. CEO salary is the natural logarithm of the total compensation the CEO received in a year. CEO Ownership is a dummy which equals 1 if the CEO has ownership in the company, 0 otherwise. CEO age is the age of the CEO measured in years. CEO is a dummy which equals to 1 if male, and 0 to female. Size and CEO Salary are adjusted for currency differences and inflation. Detailed definitions are found in the appendix.								
	Min	**Max**	**Mean**	**Median**	**Variance**	**SD**	**Kurtosis**	**Skewness**
Leverage Ratio	0.03	1.19	0.55	0.58	0.05	0.22	0.15	-0.27
Profitability	-0.98	0.42	0.01	0.04	0.03	0.18	10.77	-2.74
Size	15.67	27.76	21.44	21.38	3.63	1.90	-0.07	0.17
Tangibility	0.00	0.96	0.28	0.17	0.08	0.28	-0.54	0.89
Firm Age	0.00	148.00	30.25	16.00	1143.19	33.81	1.63	1.63
Dividend	0.00	1.00	0.35	0.00	0.23	0.48	-1.62	0.62
CEO Tenure	1.00	24.00	5.27	4.00	19.98	4.47	1.35	1.29
CEO Salary	13.02	17.90	15.02	14.97	0.49	0.70	0.15	0.24
CEO Ownership	0.00	1.00	0.04	0.00	0.04	0.19	21.48	4.84
CEO Age	25.00	72.00	48.54	49.00	55.93	7.48	-0.34	0.05
CEO Gender	0.00	1.00	0.96	1.00	0.04	0.19	20.34	-4.73
The length of the sample is N=2355 observations								

Table 2: Correlation Matrix

The table presents the correlation matrix of all relevant variables used in regressions.

	Leverage Ratio	**Profitability**	**Size**	**Tangibility**	**Firm Age**	**Dividend**	**CEO Tenure**	**CEO Salary**	**CEO Ownership**	**CEO Age**	**CEO Gender**
Leverage Ratio	1.00										
Profitability	0.01	1.00									
Size	0.24	0.31	1.00								
Tangibility	0.37	0.07	0.34	1.00							
Firm Age	0.01	0.11	0.24	0.15	1.00						
Dividend	-0.05	0.31	0.31	0.07	0.22	1.00					
CEO Tenure	-0.01	0.16	0.09	0.05	0.23	0.18	1.00				
CEO Salary	0.04	0.14	0.57	0.01	0.09	0.11	-0.01	1.00			
CEO Ownership	-0.01	-0.01	-0.16	-0.09	-0.04	0.02	0.11	-0.17	1.00		
CEO Age	0.03	0.07	0.17	0.08	0.19	0.09	0.30	0.21	0.03	1.00	
CEO Gender	0.06	-0.03	-0.03	0.00	-0.19	-0.08	-0.09	0.06	0.02	0.01	1.00

3.3.2 Other comments



Plot 1: Leverage Ratio Histogram

By looking at histograms we can get a sense of the distribution of the data. We conclude that most variables are very non-gaussian distributed. This can also be seen in table 1, descriptive stats, under reported skewness and kurtosis. We include a histogram of the leverage ratio here. See plot 1.

The descriptive stats of CEO gender shows that there are mostly male CEOs on Oslo Stock Exchange. The percentage of female CEOs in our sample was at a low of 2.18% in 2000 and has steadily increased to 6.31% in 2017. In 2003, mandatory gender quotas among the directors of the board were introduced in Norway. While this does not apply to the CEO position, we most likely see the effect as general equality improvements in the same period. The problem is that our gender variable might not give enough information about leverage because of few females in the data. We still include this variable as we expect the number and ratio of females on the exchange will continue to rise in the future.

While the central bank rate was excluded for the linear regression but included for boosting. See the appendix for Central Bank rate development. See plot 8. The annual number of companies in our sample has also gone down from 140 (2000) to 101 (2017), see appendix, plot 9.

4 Hypotheses and methodology

In chapter 4.1 we will first present the hypotheses regarding our research question. This is followed by the main methods used to answer the research question and also limitations around the methodology.

4.1 Hypotheses regarding CEO characteristics and corporate leverage

We want to research whether the CEO has an effect on leverage, so we start by asking the main research question:

Does CEO Characteristics affect financial leverage?

This main question is followed by five sub questions, which are designed to give the answer to the main. Since we research whether the CEO has an effect on leverage, we state two sided hypotheses. We also predict based on the literature what we expect the outcome to be. The key questions about CEO characteristics and leverage are:

1. How does tenure affect corporate leverage?

H_0 1: Corporate leverage is independent of CEO Tenure.

H_α 1: Corporate leverage depends on CEO Tenure.

The literature suggests that longer tenure CEOs are more confident, and the findings were that confident managers prefer internal financing (Malmendier, Tate and Yan, 2011). Frank and Goyal also found that higher tenure CEOs have less debt in the company. Consequently, we expect the same.

2. Is the CEO living the quiet life?

H_0 2: Corporate leverage is independent of CEO Salary.

H_α 2: Corporate leverage depends on CEO Salary.

We expect that CEOs with a higher salary have lower corporate leverage as the findings of Tosun (2016). The rationale is like that of equity ownership, i.e., CEOs with a high salary will act more risk averse when choosing leverage. Bertrand and Mullainathan (2003) also confirm this view, and they use the term "the quiet life" to describe the relationship.

3. How does the ownership stake of the CEO affect the leverage ratio?

H_0 3: Corporate leverage is independent of CEO Ownership.

H_α 3: Corporate leverage depends on CEO Ownership.

We follow Cronqvist, Yonker and Makhija's (2012) argument, and we argue that CEOs with equity ownership makes the CEO more careful with high leverage ratios in the company.

4. How does CEOs age impact corporate leverage?

H_0 4: Corporate leverage is independent of CEO age.

H_α 4: Corporate leverage depends on CEO age.

We expect that older CEOs are likely to have less leverage as mentioned by Cronqvist, Yonker and Makhija (2012) and the age effect of Bertrand and Schoar (2003).

5. How does gender impact the corporate leverage?

H_0 5: Corporate leverage is independent of CEO age.

H_α 5: Corporate leverage depends on CEO age.

Garcia and Herrero (2021) show that companies with a higher percentage of females on the board, have lower corporate leverage. Women are also found to be generally more risk averse (Croson and Gneezy, 2009). We also follow Frank and Goyal's (2007) findings that female CFOs are linked with lower corporate leverages.

4.2 Variable selection

To find an answer to our hypotheses we have split our methodology in two. Part 1 uses fixed industry effects, but a standard pool regression is also included. The pooled regression is found in the appendix. Part 2 uses regression trees with *gradient boosting* implemented by the package XGBoost in R. Both methodologies use the same dependent variable, the book value of debt over the book value of total assets.

$$Leverage\ Ratio = \frac{Book\ Total\ Debt}{Book\ Total\ Assets}$$

For the linear regression, we are more careful about which independent variables are included. See chapter 4.3.4 for the list of each regression model. We include models with all variables and combinations of different variables which we believe are correlated to see the change in beta-coefficients. For the boosting part, we are less concerned about what independent variables are included. We therefore include a dummy for each industry sector, and we include the central bank rate.

4.3 Regression analysis using fixed industry effects and pooled regression

To arrive at the appropriate regression models, we conduct several tests to decide between pooled OLS, time-fixed effects, entity-fixed effects, two-way fixed effects, and random effects. As a starting point pooled OLS and fixed effects will be briefly discussed, followed by a presentation of the tests conducted to choose which model is most appropriate for the data.

4.3.1 Pooled regression and fixed effects models

This chapter is based on chapter 11 in Chris Brooks Econometrics for finance from 2019. The chapters name is *Panel Data*.

The easiest way to handle unbalanced panel data is to run a classic OLS-regression. In panel-data lingo this is more precisely described as a *pooled panel regression*. Pooled OLS does not consider differences across entities or time. If there are unexplained effects across entities or industries, then we should control for this. This could be done by controlling per entity, which is known as an *entity fixed-effects* model. We simply refer to an entity fixed effects model, where the entity could mean different groups, such as company, sector, managers, etc. Two common ways to estimate the fixed effects model are via the *"Within-transformation",* i.e., demeaning each variable, or through LSDV[17] estimation. They both give the same results but have a different number of beta-coefficients.

What follows is a brief explanation of the *within transformation* for the fixed effects model. A normal OLS regression with error term u_{it}[18] assumes that there are no differences over entity. If we however assume that there are differences over entity, the error term could be written $u_{it} = u_i + v_{it}$. u_i is the individual specific effect over entity. v_{it} captures everything that is left unexplained about the dependent variable. By demeaning each variable (dependent and independent) by its entity average, we can effectively remove u_i from the equation and have a model with the unexplained heterogeneity over entity. It is possible to do the same using the time mean. The procedure is the same as the within-transformation for the entity fixed model but differs in the fact that the time-mean is used as the demeaner.

Alternatively, the same model could be estimated using LSDV, and that is simply done by including a dummy variable for each entity. In this case, entity would be the individual company. This means that the model includes 303 dummy variables, one for each firm[19]. If the average value of y_{it} changes across time, and we want to control for the time aspect (Brooks, 2019, p.495), we can instead use 17 year-dummies. Then the model is a time-fixed-effects model. Both cases using LSDV give a high number of dummy-variables, which can be hard to interpret.

[17] LSDV = Least Square Dummy Variable
[18] i for specific entity and t for time.
[19] Remember that the data is unbalanced, so this varies over time if one were to look at a specific year.

If it is necessary to control for both entity and time, then we have a two-way model. This can be done by within transformation on both time and entity simultaneously, or simply including entity and time dummies simultaneously using LSDV. As mentioned in chapter 3 we adjusted "nominal money" variables for inflation, so we expect that a lot of the variation across time is removed. That includes CEO salary and Size.

We do not consider using a random effects model after conducting a Hausman test. We do not elaborate more on this model.

4.3.2 Statistical tests for model choice

The following chapter presents statistical tests which can be conducted to choose the correct model. This is a purely quantitative way of choosing the model. While this method is not failproof, in chapter 4.3.3 we discuss the economic rationale behind the model choice. Stock and Watson (2020), Brooks (2019), Green (2008, chapter 9) and the recipe of Oscar Torres-Reyna of Princeton University (2022) help us compile a procedure and helps us choose between pooled, fixed industry-effects, time fixed effects and random-effects. We create all 8 models mentioned in chapter 4.3.4, and make a pooled, fixed industry, time fixed and random effects equivalent. We will not summarize the individual hypothesis test-results but provide a brief description of the outcome as they give the same result.

First, we conduct an *F-test* for Pooled vs. Fixed Industry Effects. We reject the null of pooled model and conclude that a fixed effect is better. *Second*, we conduct a Breusch-Pagan Lagrange Multiplier-test for pooled vs. random effects. We reject the null hypothesis and find that a random effects model is better suited. *Third,* we conduct a Hausman-test for fixed industry effect vs. random effect (Brooks, 2019, p. 823). We reject the null hypothesis and find that fixed industry effects are the best for our data. *Fourth,* and lastly, we conduct two more Breusch-Pagan-test, one for fixed industry vs. fixed time effects and fixed industry vs. two way fixed. We are not able to reject the null hypothesis for any of the two, and we conclude that an industry fixed effect model is the best choice.

Also, Brooks (2019, p. 502) defines that if you expect the entities in the sample to be randomly selected from the population, the random effects model is better. If the opposite is true, fixed effects is better. Some observations have been excluded due to NAN-problems, but we still believe that the fixed effects model to be the better choice.

What follows is a check of the classical OLS assumptions. The fixed effects assumptions are very similar according to Stock and Watson (2020, p 375). We start to check the normality assumption and by looking at the histograms we conclude that we have several variables which are particularly non-normal distributed. Several variables are non-normal distributed, even after log transformation. We then conduct a Breusch-Pagan-Test for heteroskedasticity. Heteroskedasticity is present in all our models. We then use a Breusch-Godfrey test for serial correlation[20] in panel models concludes that we have autocorrelation in all models estimated. By looking at the correlation matrix we conclude that none of the variables are perfectly correlated, indicating non-perfect multicollinearity, even though CEO salary shows some correlation with size. Since both Heteroskedasticity and autocorrelation is present in our data we must produce H.A.C.[21] standard errors (Stock & Watson, 2020, p. 374-376). Brooks (2019, p. 279) proposes to use *Newey-West Heteroskedasticity and Autocorrelation robust standard errors* (Newey and West, 1987). We conclude that we use Newey-West standard errors.

4.3.3 Economic rationale for model choice and conclusion

We argue that the leverage ratio moves very little over the sample period from 2000 to 2017, or at least is mean-reverting. See plot 6 in the appendix, *"Heterogeneity across time"*. This rules out the time fixed effect model. The differences between industries might be greater, which we check. While the average leverage is within an 8% range for time, the range between sectors is almost 20% ranging from 0.5 to 0.7[22]. See plot 7 in the appendix, *"Heterogeneity across industries"*. We argue for the use of a fixed industry effects model. Company fixed effects could alternatively be used, but we believe that using industry fixed effects is sufficient for the study.

[20] Serial correlation is a synonym for autocorrelation.
[21] Alternatively, these are called H.A.R. errors.
[22] This does not include financials, because by doing so the difference is well above 30%.

Cronqvist, Yonker and Makhija (2012) is using Industry fixed effects. Bertrand and Schoar (2003), use company, time and manager fixed effects. Our dataset let us not identify individual CEOs, so we are not able to use manager fixed effects. Malmendier, Tate and Yan (2011) use time, company, and industry fixed effects in their study. Some scholars also point to the use of lagged variables in their regressions (García de Olalla, 2014). Since we study book values, and not market values, we do not include any lagged variables in our main model. A lagged model is used as a robustness check.

Both the statistical tests and economic rationale point in the direction of using fixed effect models. We also include a pooled regression for comparison to the industry fixed effects.

4.3.4 Regression models

LR is short for Leverage Ratio. See chapter 3.2 or appendix for variable definitions. Model 1) is testing our hypotheses regarding all variables at hand.

1) $$LR = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Profitability + \boldsymbol{\beta_2} Size + \boldsymbol{\beta_3} Tangibility + \boldsymbol{\beta_4} Firm\ Age + \boldsymbol{\beta_5} Dividend + \boldsymbol{\beta_6} CEO\ Tenure + \boldsymbol{\beta_7} CEO\ Salary + \boldsymbol{\beta_8} CEO\ Ownership + \boldsymbol{\beta_9} CEO\ AGE + \boldsymbol{\beta_{10}} CEO\ GENDER + u$$

Model 2) is testing the potential multicollinearity issue between Size and CEO salary. We remove size, to see the effect of CEO salary alone. Model 3) is testing whether CEO age and gender has an effect on LR. Model 4) is testing whether salary and ownership have an effect on LR.

2) $$LR = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Profitability + \boldsymbol{\beta_2} Tangibility + \boldsymbol{\beta_3} Firm\ Age + \boldsymbol{\beta_4} Dividend + \boldsymbol{\beta_5} CEO\ Tenure + \boldsymbol{\beta_6} CEO\ Salary + \boldsymbol{\beta_7} CEO\ Ownership + \boldsymbol{\beta_8} CEO\ AGE + \boldsymbol{\beta_9} CEO\ GENDER + u$$

3) $$LR = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Profitability + \boldsymbol{\beta_2} Size + \boldsymbol{\beta_3} Tangibility + \boldsymbol{\beta_4} Firm\ Age + \boldsymbol{\beta_5} Dividend + \boldsymbol{\beta_6} CEO\ AGE + \boldsymbol{\beta_7} CEO\ Gender + u$$

$$4)\ LR = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Profitability + \boldsymbol{\beta_2} Size + \boldsymbol{\beta_3} Tangibility + \boldsymbol{\beta_4} Firm\ Age + \boldsymbol{\beta_5} Dividend + \boldsymbol{\beta_6} CEO\ Salary + \boldsymbol{\beta_7} CEO\ Ownership + u$$

Model 5a) is run as a consistency check on model 1), only including the control variables. In model 5b we regress the residuals from 5a) on the CEO characteristics. The idea is that whatever is left unexplained from the control variables, should be accounted for by the CEO characteristics. We would like to see that the CEO characteristics are still significant and keep coefficient size and sign. This approach is the same as Pulvino (1998, p. 955) used.

$$5a)\quad LR = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Profitability + \boldsymbol{\beta_2} Size + \boldsymbol{\beta_3} Tangibility + \boldsymbol{\beta_4} Firm\ Age + \boldsymbol{\beta_5} Dividend + \boldsymbol{u}^*$$

$$5b)\quad \boldsymbol{u}^* = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} CEO\ Tenure + \boldsymbol{\beta_2} CEO\ Salary + \boldsymbol{\beta_3} CEO\ Ownership + \boldsymbol{\beta_4} CEO\ Age + \boldsymbol{\beta_5} CEO\ Gender + u$$

We estimate these 6 models in 2 combinations: fixed Industry Effects using the LSDV method[23] and pooled regressions. While the fixed sector model is of main interest, we include a pooled model too see what happens if we exclude fixed effects on sector (see appendix table 8 and 9). Cronqvist, Yonker and Makhija (2012) uses both pooled regression and the fixed industry effects for their study. We follow their model choice.

4.4 Other Robustness checks

We also introduce two additional robustness checks to see what happens if we choose a subsample and do the same regression as model 1), both for pooled and fixed.). We exclude observations before 2005 and after 2015. This model is called 5c). The last robustness check is also done on model 1), both pooled and fixed, but the independent variables are lagged by one year. This is to control for some endogeneity issues, which

[23] Alternatively, using the *plm* package in R, all the models could be estimated there. However, plm does not support Newey-West standard errors (HAC-robust errors).

can be read about in chapter 4.6. Here we include all observations from the original sample, but due to lagging we lose 324 observations. This model is called 5d).

4.5 Extreme Gradient Boosting - Machine learning using XGBoost in R

As an alternative to traditional linear regression, we wanted to try an alternative machine learning approach. OLS, being a linear model type is more likely to fail describing non-linear relationships between dependent and independent variables. An example would be trying to fit a straight line through a sinewave. It is not possible to achieve an R squared of 100%, as the data-generating process (DGP) is a "curly wave" and not a straight line. Another problem with the linear regression model is that multiple assumptions need to hold to produce a good prediction[24]. The strength of OLS is that it is highly interpretable, and by looking at the sign and size of the beta coefficients it is possible to get an economic interpretation of each variable. However, the crucial weakness is OLS's ability to model *interaction effects*, which more complex models are designed for. Specifying interacting effects using OLS across time, companies/industries, control variables and CEO characteristics variables, is hard and will quickly become unwieldy as the number of coefficients needed is high. A more complex model is needed to produce such a result. The choice of this model comes at a cost, *the interpretability vs. flexibility tradeoff*. James et.al (2014, p.25) present the tradeoff visually in a plot. In short, models that are easy to interpret, such as ordinary linear regression and Subset Selection Lasso, are not very flexible. This could be assumptions of the model or simply not being able to capture the true data generating process, i.e., linear regression example. On the other extreme, we have models that are very flexible such as KNN, boosting and Neural Networks, which are hard to interpret. Somewhere in the middle we find Generalized Additive Models (GAM).

Any form of statistical model is based in one of two cultures (Breimann, 2001). The Machine learning/algorithmic and the inference/traditional statistics-based culture. The algorithmic treats the data mechanism as unknown, while the inference-based assumes that *"the data is given from a stochastic data model*" (p.199). The algorithmic culture

[24] Linearity in parameters, residual mean of 0, no heteroskedasticity, no autocorrelation, error terms are normally distributed, and no multicollinearity.

can be summarized in that it only cares about prediction, and less about the inference/interpretation between variables. Thus, the algorithmic culture is all about optimizing the accuracy of the model, i.e., having a high R Squared or low RMSE. The inference based is more interesting in applying an interpretation to the results, and not necessarily all about getting the most precise prediction.

For our thesis we chose to incorporate a version of the machine learning technique *"regularized and boosted regression trees"*, using the R-implementation XGBoost (eXtreme Gradient Boosting). It is a free and open software designed by Tianqi Chen and Carlos Guestrin. The software is based on the original XGBoost paper: *XGBoost: A scalable Tree and Boosting System* from 2016. We will limit our thesis to not include the derivations of XGBoost, thus leaving that to the authors Chen and Guestrin. We will however explain the software at a basic level and show that by choosing the right *hyperparameters* we can vastly improve the R squared of our OLS regressions. XGBoost output predicted values of leverage by using a random test-training split. We can measure the accuracy of the prediction by various machine learning performance measures. We are also able to interpret the *"importance matrix"*, look at *Shapley-values* and interpret the different *SHAP-value plots*. While the process of XGBoost/the prediction remains a *"black box*[25]*"*, we can predict and get some non-linear connections between the independent variables and the Leverage Ratio.

4.5.1 How XGBoost works and its interpretation

XGBoost is composed of two concepts, *decisions trees* and *gradient boosting*. Decision trees can be used for classification, i.e., deciding if a new datapoint is red or blue in color classification, or to spot a cancer cell among normal cells. It can also be used for regression, where you predict a y-value based on different x-variables. Both classification and regression work by splitting the dataset into if-else statements, i.e., the decision tree. To explain decision trees, we use an example of classification[26]. Classification means to classify new data points based on a previous data set. If you

[25] The human mind will struggle to come up with a reasonable explanation for why XGBoost calculates a given prediction, i.e., the process of XGBoost is considered a black box.
[26] *Classification is NOT the method we use, but classification is easier to visualize and understand than regression. See next section for description of our method.*

have a dataset with red and blue points, we want by looking at different known characteristics of the new data points, to decide if a particular point is red or blue. If a known characteristic about the *known points* is measured continuously between 0 and 20, we could start the tree by splitting the data into 2 groups. This could be above or equal to 12 and below 12, or in mathematical terms x>= 12. In decision tree-lingo, the two new groups are called *leaf-nodes*. We continue splitting down the tree (creating new nodes) until we only have red or blue points in a leaf-node. This is where the classification happens, because by looking at a new data point with equal characteristics as the ones you know in this group, you can classify the new point[27]. It is possible to create many different splits depending on where you set the initial split. But what splits are optimal? The fever leaf-nodes the better. This is done by calculating the "entropy" of each split and the "information gain" of each split.

$$Entropy = E = \sum (-p_i \, log_2(p_i))$$

Where $p_i = \ probability \ of \ class$

If there are 50 blue and 50 red points in the parent-node, then p_{red} = 0.5 and p_{blue} = 0.5 because there is an equal probability of being either red or blue. We calculate the entropy for the parent leaf-node, and then for each split under consideration. When p is 0.5 for both of the classes, then the entropy equals 1 which is the highest possible entropy. We then calculate the information gain, IG, for all the splits under consideration (which can be as many as you like):

$$IG = E(parent) - \sum w_i E(child_i)$$

w_i is the number of observations in the child node, relative to the parent node. So, if there are 15 observations in one of the child nodes, and 20 in the parent, the weight is $\frac{15}{20} = 0.75$. $\frac{5}{20} = 0.25$ is the weight of the other child node. The split under the parent

[27] One of the authors of the original XGBoost paper proposed to use the method for predicting Higgs Boson in a machine learning competition. The method landed them among the 2% best in the competition. (Chen and He, 2014)

node which maximizes IG, is the split that is chosen. When using packages in R, Python or other languages, all splits within certain boundaries are considered. The weakness of decision trees, being a *greedy* algorithm, is that the node splits are not recursive. The consequence is that there can (and most likely will) exist a more optimal decision tree. This is where the *boosting* part of XGBoost comes in. By combining the predictions of multiple trees into one, the model is improved by giving more weight to predictors that perform better.

Our dataset has continuous variables, and we cannot use classification for prediction. *We use regressions trees, rather than classification trees*. The idea for *regression*, is almost similar, but instead of calculating entropy and information gain, the software chooses the splits that minimize the mean square value, MSE.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2$$

The prediction value within the last node, is simply the average of the values within that node, thus creating jagged nonlinear line which regression trees are known for. XGBoost has been optimized for big tabular data sets and can handle billions of observations and many independent variables, due to its greedy nature. It can handle outliers/leverage points[28] and missing observations very well. XGBoost also automatically does feature[29] selection, such that it will automatically rank the most important features. Financial data often have a very low signal to noise ratio[30], thus trying to predict stock returns, is notoriously difficult to achieve. Gu, Kelly, and Xiu (2020) test various portfolio return predictions ranging from different Neural Networks[31], boosted trees and OLS. Their best performing portfolios came from Neural Networks and boosted trees, and as they claim, doubled the portfolio returns of OLS.

[28] Outliers and leverage points are different terms, but often used to describe the same: A big, abnormal observation that can ruin the model's prediction. I.e., OLS is very sensitive to outliers.
[29] Feature is another word for independent variables in machine learning lingo.
[30] Measured by R Squared.
[31] Another common machine learning technique.

A key weakness of XGBoost, as opposed to OLS, is that XGBoost is not able to extrapolate outside the data points it has already seen. If there is a linear relationship between the dependent and independent variables, OLS will extrapolate very well, by inserting *out of sample data* points that are bigger/smaller points than the original data set. We can however by looking at the *importance matrix* produced by XGBoost, decide what variables/features are the most important. This matrix contains 3 feature performance measures, and each method ranks the features differently by "importance". Towardsdatascience.com (2018), explains the different measures. We summarized the explanation in table 3. There is no clear reason why one measure will be chosen over another, but it would depend on the data, i.e., continuous, binary, discrete etc. Without referring to any specific papers or web pages, we see that *gain* is the most widely used. A fourth possibility is to use SHAP[32]-values. The idea is based on the economist Lloyd Shapley, who presented the idea of Shapley values for game theory to see which "player" contributed the most towards the outcome of a "game". Lundberg and Lee (2017) took the idea further and established a machine learning equivalent. The method allows us to visualize feature importance in the form of "*Bee swarm plots*" and "*dependency plots"*. Bee swarm plots ranks feature importance from lowest to highest, while looking at each individual features contribution to the dependent variable (at observation level). We are able to see each individual observation's contribution to the leverage ratio in the form of Shapley-values. The values are interpreted as "the marginal contribution" towards leverage. A dependency plot plots an independent variable's value on the x-axis, and its SHAP-value on the Y-axis per observation. This allows us in detail to see non-linear trends in the contribution towards the dependent variable. For more information about practical SHAP plot interpretation, see Aidan Cooper's webpage/article (2022).

[32] Abbreviation for SHapley Additive exPlanations

Table 3: Interpretation of Importance matrix	
Weight	The number of times a feature is used to split the data across all trees.
Cover	The number of times a feature is used to split the data across all trees is weighted by the number of training data points that go through those splits.
Gain	The average training loss reduction gained when using a feature for splitting.
SHAP	Calculates a SHAP-value for feature importance. Interpretated as the marginal

We use both an importance matrix (ranked by gain) and SHAP-plots for understanding the relationship between CEO Characteristics and the Leverage Ratio proposed by XGBoost. Please note that the dependency plots must be carefully interpreted at the edges of the plot, where the number of observations is lower.

4.5.2 Cross validation, hyperparameters of XGBoost and model optimization

In this chapter, we refer to XGBoost R documentation which can be found online (XGBoost R Tutorial, 2021), or in R after installing the package XGBoost under help.

The goal of any machine learning is to reduce an error measure, i.e., the difference between the predicted[33] and actual values. A common measure is that of the root mean square error, RMSE.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y} - y_i)^2}{n}}$$

Alternatively, R squared can also be used. A RMSE of 0 would indicate that the prediction fits perfectly, and there is no error between the training data and test data. RMSE is in the scale of what we are trying to predict, i.e., when predicting leverages the RMSE will be in terms of percentages[34]. When training XGBoost, it is normal to split into a training sample and a test sample. This is because it is hard to measure the accuracy of the model without knowing what prediction one was supposed to reach. An 80% training (also called in sample) and a 20% test (also called out-of-sample) are

[33] Predicted and fitted values are used interchangeably.
[34] A way of standardizing RMSE, would be to calculate «Normalized RMSE». Normalized RMSE will always be between 0 and 1, thus standardizing the measure on scale.

commonly used. Multiple problems can occur by doing this. The split is typically random, which means that if the data are not independent and identically distributed (IID) random variables, we might see that there is a big variance in the results depending on the split. From a time-series perspective, there could be certain paradigm shifts in the data, i.e., the financial crisis of 2008. What training and test split could make a difference if the modeler believes there is a change in the data at a certain point in time.

When modeling we must take into consideration that the model can fit the training data well, but not the test. This is known as having a *high bias*. If there is a lot of variability when using different test-training splits, the model has *high variance.* A common way to alleviate what is known as the *bias-variance tradeoff* is through *cross-validation.* A 10-fold cross validation would imply making 10 different training-test splits, run the model on each of those, and take the average prediction of the 10 predictions. This is implemented in XGBoost, and we use a 10-fold cross validation to make our results more robust against a wrongly chosen training-test split[35].

To optimize the model, XGBoost comes with different *hyperparameters* that can be tweaked to produce the lowest RMSE possible. We will briefly introduce the most used: *max depth, nrounds, early stopping rounds, eta, lambda, and gamma.* Max depth is the "height" of the tree, i.e., the maximum number of rows where splits can happen. Depth of 6 is the default value and note that XGBoost not necessarily will produce 6 levels here. Nrounds is the number of trees that XGBoost produces. Early stopping rounds has to do with preventing *overfitting*[36] by finding the best tree with the lowest RMSE by stopping after RMSE not has been improved for nrounds rounds. 20-50 is common but depends on the complexity of the data. Eta is the learning rate and controls the contribution of the boosting part of XGBoost. The default value is 0.3, but a lower value can be chosen. At the same time, nrounds must be increased as XGBoost uses

[35] In the time-series perspective, have a rolling forecasting window, might be a better option. This implies, as time goes on, increasing the number of observations in the training data, or «moving the window»

[36] Overfitting describes a situation where the model has been trained «too well», i.e., producing an exceptionally low RMSE for the training set, but the model is not able to account for unseen/new values.

more trees to get the prediction. For very large and complex datasets, eta must typically be increased to lower the computational time. We do not expect issues with that in our thesis. Lambda controls the regularization and has the same interpretation as lambda in RLS (Regularized Least Squares). Lambda equal to 1 means no regularization and is the standard value. Gamma is *"the minimum loss reduction required to make a further partition on a leaf node of the tree"* says the XGBoost-documentation. The default setting is 0. By experimenting with these values, we can find an optimal combination of hyperparameters such that RMSE is minimized. This can be done manually or by using the XGBoost function *gridsearch* which allows multiple tests of hyperparameters at the same time while running cross validation. We will publish our hyperparameter settings and results in chapter 5.

4.6 Limitations of our study

In general, the number of observations would be high enough for the linear regression. XGBoost would most likely do even better with a higher number of observations, especially for CEO Gender and CEO Ownership. We also have to consider *endogeneity* in our study, and in the following sections we will discuss the endogeneity problem and potential solutions. We are partially dealing with the problem, but some parts are not possible to handle and must be left to a discussion. The three sources of endogeneity are *omitted variable bias, simultaneity/reverse causality* and *measurement error*.

Omitted variable bias is something that we tackle by using previous research on capital structure to find relevant variables that is considered important in explaining leverage ratio. However, we are still left with CEO characteristics that we were not able to collect, such as CEO education, CEO reputation, CEO home leverage, CEO overconfidence etc., and other control variables. We do however not expect these variables to have such an impact that we are not able to consistently estimate the coefficients.

Simultaneity or reverse causality is the second source of endogeneity. We need to consider four questions to say whether we could claim that there is a causal relationship between leverage and the independent variables. The discussion follows Kellstedt and Whitten (2018, p 56-74).

1) *Is there a credible causal mechanism that connects X to Y?*

   The CEO controls the agenda for the company and decides within his mandate what actions that should be taken for the company to reach its goals. The CEO does not have the opportunity to decide the capital structure of the company on his own, but material brought forward for the board and owners are controlled by the insiders in such a way that we would expect that CEOs have an impact on the financing decisions for the firm.

2) *Can we rule out the possibility that Y cause X?*

   This question is considered in model 5d when we lag all explanatory variables. This is not considered to completely rule out the possibility that the leverage ratio could explain any of the explanatory variables. This is due the fact that the dependent variable could be very close to its previous value and give similar results to that of not lagging.

3) *Is there covariation between X and Y?*

   The Correlation matrix is created to answer this question. There is low to very low correlation between all variables and leverage ratio except for size and tangibility. This does not however rule out variables that have low correlation, and there is a possibility that a causal relationship does exist even though low correlation is present. It might be that a control variable is necessary before we see a relationship between the two variables (Kellstedt and Whitten, 2018, p 63).

4) *Have we controlled for all cofounding variables Z that might make the association between X and Y spurious?*

   Having included the variables that are known from other research papers to be the most important when it comes to explaining leverage ratio, we conclude that we do not leave out variables that explain both X and Y.

The third source of endogeneity is Measurement error. Since we are dealing with accounting numbers, we had to adjust for inflation and currency. There are still differences in how companies report numbers across firms and industries. There are major and minor regulatory changes every year, such that a precise comparison over time, is very difficult to make. Predicting CEO salary because of missing values could also lead to measurement errors.

5 Results and main analysis

This section will present regressions that are constructed to look into the main research question, “Does CEO Characteristics affect financial leverage?”. The following will start by presenting the results from the fixed effect models (see table 4) and the corresponding robustness checks (table 5). This will be followed by a presentation of the XGBoost results (table 6).

The control variables[37] are included in all the models presented in this thesis, except for size in model 2. The results from the pooled regressions, and the pooled robustness check, can be found in the appendix (table 8 and 9). A discussion of our overall results will follow the presentation of the fixed effect model and XGBoost.

5.1 Industry Fixed Effect results

The discussion of our results will first look at determinants of capital structure up to the theories of capital structure[38] presented in the literature review. This is then followed by a discussion of the results with the hypotheses asked regarding the relationship between CEO characteristics and capital structure in mind. Model 1) include all CEO characteristics. Model 2 excludes size. Model 3 and 4 exclude different CEO characteristics to see whether the coefficients are significant after the change. See next page for table 4.

[37] Profitability, Size, Tangibility, Firm Age, and Dividend
[38] Tradeoff theory, pecking order theory, and free cash flow theory

Table 4: Industry Fixed Effects Regression results

This table reports the coefficients and standard errors from 4 different fixed Industry Effects regressions with the Leverage Ratio as dependent variable and determinants of capital structure and CEO characteristics as independent variables. We used the LSDV fixed effects method for calculating the beta coefficients, and that is using a dummy variable for each industry. The 8 dummies have all been omitted for the sake of table readability. We have included the intercept, but dropped industry code 1, to avoid the dummy variable trap and to replicate the coefficients a within transformation. The financial sector is not included in the sample. The sample consists of 303 Norwegian listed companies in the period 2000 to 2017. All variables are compiled from the CCGR database provided by BI Norwegian Business School in 2022. The Leverage Ratio is defined as book total debt to book value of total assets. Profitability is the company's Return on Assets (ROA) and is defined as after-tax earnings before interest (EBI) to book value of total assets. Size is the natural logarithm of book total assets. Tangibility is defined as the ratio of book tangible assets to book total assets. Firm Age is the company's age measured in years. Dividend is a dummy equal to 1 if the company pays dividends, 0 otherwise. CEO Tenure is the time in years which the CEO has worked in that position. CEO Salary is the natural logarithm of the CEO's total salary, bonuses, options etc. CEO Ownership is a dummy equal to 1 if the CEO has ownership in the company, 0 otherwise. CEO Age is the CEO's age measured in years. CEO Gender is a dummy equal to 1 if male, and 0 otherwise. The standard errors are in parentheses and are Newey-West heteroskedasticity and autocorrelation robust standard errors. Significance levels are denoted by *, **, ***, which corresponds to 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Profitability	**-0.040**	**0.0002**	**-0.035**	**-0.039**
	(0.035)	(0.036)	(0.035)	(0.034)
Size	**0.024*** **		**0.018*** **	**0.023*** **
	(0.004)		(0.003)	(0.004)
Tangibility	**0.267*** **	**0.316*** **	**0.278*** **	**0.271*** **
	(0.023)	(0.020)	(0.022)	(0.023)
Firm Age	**-0.0003** **	**-0.0002**	**-0.0003** **	**-0.0003*** **
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Dividend	**-0.063*** **	**-0.049*** **	**-0.060*** **	**-0.064*** **
	(0.009)	(0.009)	(0.009)	(0.009)
CEO Tenure	**-0.00004**	**0.0001**		
	(0.001)	(0.001)		
CEO Salary	**-0.022*** **	**0.010**		**-0.020** **
	(0.008)	(0.006)		(0.008)
CEO Ownership	**0.042* **	**0.032**		**0.043* **
	(0.023)	(0.023)		(0.023)
CEO Age	**-0.0001**	**-0.0001**	**-0.0003**	
	(0.001)	(0.001)	(0.001)	
CEO Gender	**0.056** **	**0.049** **	**0.052** **	
	(0.024)	(0.024)	(0.024)	
Intercept	**0.238** **	**0.289*** **	**0.055**	**0.275*** **
	(0.101)	(0.099)	(0.078)	(0.098)
INDUSTRY FIXED EFFECTS	**YES**	**YES**	**YES**	**YES**
Observations	**2355**	**2355**	**2355**	**2355**
R^2	**0.214**	**0.195**	**0.210**	**0.212**
Adjusted R^2	**0.209**	**0.189**	**0.205**	**0.207**

5.1.1 Control Variables

Profitability is not significant in our regression models. This does vary from research conducted on the same data[39], but we however find a possible explanation in the preparation of the data. Several studies limit their data to companies with sales above a certain amount of monetary threshold. We do not limit our data in this way because it could lead to a survival bias in our data. The sign for the variable profitability suggests that more profitable companies should have lower leverage ratios. This is consistent with the pecking order theory, but no meaningful value could be drawn because of the lack of significance.

In sync with the tradeoff theory and the market timing theory we find that the coefficient of size has a positive impact on leverage ratio. An explanation could be that larger companies are more diversified and much of the costs associated with financial distress is fixed which gives relatively lower deadweight cost for larger companies. Larger companies tend to be older, more stable, have a record of “good behavior” and have a longer period of positive earnings. We believe that this leads to better terms in the capital markets.

We find that companies with a larger proportion of tangible assets have higher leverage ratio. This is consistent with the tradeoff theory; we believe that the possibility to put up collateral is the major driver for this result. Having leverage tied to physical assets limit the bankruptcy costs and the asymmetric information problem that is present between the lender and the borrower.

Firm age is found to have an effect that is -0.03% times the age of the firm on the leverage ratio. The sign has shifted from the correlation matrix where we had correlation close to zero of 0.01. The regression result is consistent with the pecking order theory because older firms are usually bigger and have the possibility to retain earnings. The result and argument contradict the discussion regarding firm size.

[39] Data from the CCGR database. Garcia de Olalla (2014) and others.

The last control variable is a dummy variable equal to one if the firm pays dividend in the given year and zero if not. We find that dividend paying firms have lower leverage ratio than that of non-dividend paying companies. The argument supporting this is that dividend paying firms limits the free cash flow problem by committing to dividends, instead of debt. Further on it is possible to imagine a profitable company with fixed capital investments and fixed dividend payments, if ROA stays constant as well, we expect the leverage ratio to become lower.

5.1.2 CEO characteristics

CEO Tenure is found to be insignificant, and its contribution towards leverage is slightly negative, but very close to zero. The sign is the same as Frank and Goyal (2007), but they used market values as opposed to book values of leverage.

The sign of CEO Salary is found to be negative and significant. CEO salary is the natural logarithm of the CEOs compensation, such that a 100% increase in CEO salary is related to a $\mathrm{LN}(2) \cdot -0.022 = -0.01525$ or -1.525% decrease in the corporate leverage. This could mean that higher paid CEOs might prefer “the quiet life”, and when reaching a higher salary, they decrease the financial risk of the company to avoid losing the benefits they have obtained. It can be hard to get a high salary in another company.

A counterargument is the market for corporate control proposed by Henry Manne (1965); management of a poor performing firm could see their firm be a target for a hostile takeover. This could be enough to ensure that management runs the firm in the interest of shareholders such that the CEO could hold on to the position for longer. Because of the high correlation between Size and CEO salary we remove Size to see which effect this would have on CEO salary in model 2). This changes CEO salary to having no significant effect. We do however have an omitted variable bias in the model when size is removed.

CEO ownership is significant at a 10% level and is positively related to leverage. Having ownership in the company suggest that the company should have a 4.2% higher leverage than if the manager does not have ownership. This relationship could be due to the fact that the manager is aligning his incentives if he has ownership, and therefore taking advantage of the tax shield available to the company.

The sign is negative, and the beta coefficient is very small for CEO Age. It is not significant at any levels. Hence, we are not able to confirm that the age of the CEO affects the leverage. It might be because most CEOs are quite concentrated in age, typically ranging from 40 to 60 years old.

CEO gender is found to be significant at a 5% level and being male is linked with a 5.6% increase in leverage. This confirms Frank and Goyal's (2007) and our view that male CEOs tend to have higher leverage ratios in their companies. As Croson and Gneezy (2009) found in their research that women are generally more risk averse than their counterparts. In our regressions, we find that female CEOs are more careful when it comes to financial risk because they take on lower leverage ratios. This is consistent across all models in table 4.

5.1.3 Regression robustness checks

Chapter 5.1.2 introduced 4 different models, where model 2), 3) and 4) is robustness checks of model 1). We see that the change in beta coefficients is very small, and the sign stays constant across all variables, except for model 2 where we remove Size to see how this impacts the model at hand.

Table 5: Regression robustness results from industry fixed regressions

This table reports the coefficients and standard errors from 3 robustness checks. The dummy variables for industry sector have been excluded for readability. We have included the intercept, but dropped the first dummy, to avoid the dummy variable trap and to replicate the coefficients a within transformation. The 8 dummies have all been omitted for the sake of table readability. Model 5a) uses Leverage Ratio as the dependent variable and capital structure control variables as independent. 5b) uses the residuals from 5a as the dependent variable, and different CEO characteristics as independent variables. 5a) and 5b) is equivalent to a residual-regression-robustness check proposed by Pulvino (1998, p. 955). Model 3) refers to a subsample between 2005 and 2015 as a robustness check. Model 4) uses 1 year lagged independent variables. All variables are compiled from the CCGR database provided by BI Norwegian Business School in 2022. The Leverage Ratio is defined as book total debt to book value of total assets. Size is the natural logarithm of book total assets. Tangibility is defined as the ratio of book tangible assets to book total assets. Firm Age is the company's age measured in years. Dividend is a dummy equal to 1 if the company pays dividends, 0 otherwise. CEO Tenure is the time in years which the CEO has worked in that position. CEO Salary is the natural logarithm of the CEO's total salary, bonuses, options etc. CEO Ownership is a dummy equal to 1 if the CEO has ownership in the company, 0 otherwise. CEO Age is the CEO's age measured in years. CEO Gender is a dummy equal to 1 if male, and 0 otherwise. The standard errors are in parentheses and are Newey-West heteroskedasticity and autocorrelation robust standard errors. Significance levels are denoted by *, **, ***, which corresponds to 10%, 5%, and 1% levels, respectively.

	5a)	5b)	5c) FIXED SUBSAMPLE	5d) FIXED LAGGED
Profitability	**-0.035**		**-0.033**	**-0.0040**
	(0.035)		(0.045)	(0.040)
Size	**0.018*** **		**0.020*** **	**0.027*** **
	(0.003)		(0.005)	(0.005)
Tangibility	**0.282*** **		**0.272*** **	**0.213*** **
	(0.022)		(0.025)	(0.029)
Firm Age	**-0.0003*** **		**-0.001*** **	**-0.0005** **
	(0.0001)		(0.0002)	(0.0002)
Dividend	**-0.061*** **		**-0.068*** **	**-0.069*** **
	(0.009)		(0.011)	(0.011)
CEO Tenure		**-0.0002**	**0.001**	**-0.000006**
		(0.001)	(0.001)	(0.0014)
CEO Salary		**-0.018*** **	**-0.008**	**-0.027*** **
		(0.007)	(0.009)	(0.010)
CEO Ownership		**0.038***	**0.056**	**0.051***
		(0.023)	(0.039)	(0.030)
CEO Age		**-0.00004**	**0.0005**	**-0.001**
		(0.001)	(0.001)	(0.001)
CEO Gender		**0.058** **	**0.064** **	**0.053**
		(0.024)	(0.025)	(0.033)
Intercept	**0.097**	**0.192***	**0.080**	**0.291** **
	(0.074)	(0.100)	(0.124)	(0.127)
Industry Fixed EFFECTS	**YES**	**YES**	**YES**	**YES**
Observations	**2355**	**2355**	**1491**	**2031**
$\boldsymbol{R^2}$	**0.208**	**0.053**	**0.231**	**0.193**
Adjusted $\boldsymbol{R^2}$	**0.203**	**0.048**	**0.222**	**0.186**

Model 5a) and 5b) (table 5) give the results of a robustness check of the residuals of the control variables run on the CEO variables. We see that the sign and size of the CEO characteristic variables in model 5b) looks similar to that of model 1), when they were regressed on the residuals from model 5a). Further, we look at model 5c), which is a subsample between 2005 and 2015 with 1491 observations. The results are similar to that of model 1). With one exception, CEO salary changes from being significant at a 1% level, to not being significant at all. 5d) explores what happens when we lag all the independent variables by 1 year, and the results are similar. Gender is no longer significant at any level. The pooled equivalents of the industry fixed effects are presented in table 8 for the pooled regression and find that these results are close to identical. We are confident that the results are robust over different samples, time and combinations of variables.

5.2 Results from Gradient Boosting using XGBoost

After using the following hyperparameter tunings for our dataset; Max Depth = 6, Objective = Squared error, nrounds = 2500, Early stopping rounds = 50, Lambda = 1 and Gamma = 1 we were able to obtain the following predictive results:

Table 6: Common Machine learning accuracy measures

MSE	**MAE**	**MAPE**	**RMSE**	R^2
0.0217	0.1092	0.4443	0.1475	0.557

We see that by implementing XGBoost to predict leverage increases R squared from 0.214 in regression model 1) to 0.557. Table 7 presents the results from the importance matrix. It is possible to see that our control variables are found to be the most important variables when explaining the leverage ratio for a company. For this model, we included the central bank rate, and find that it is ranked number 9 by importance. It is beaten by most other control variables and CEO characteristics except Dividend, CEO Gender and CEO Ownership. This confirms the view of not being very important for predicting leverage.

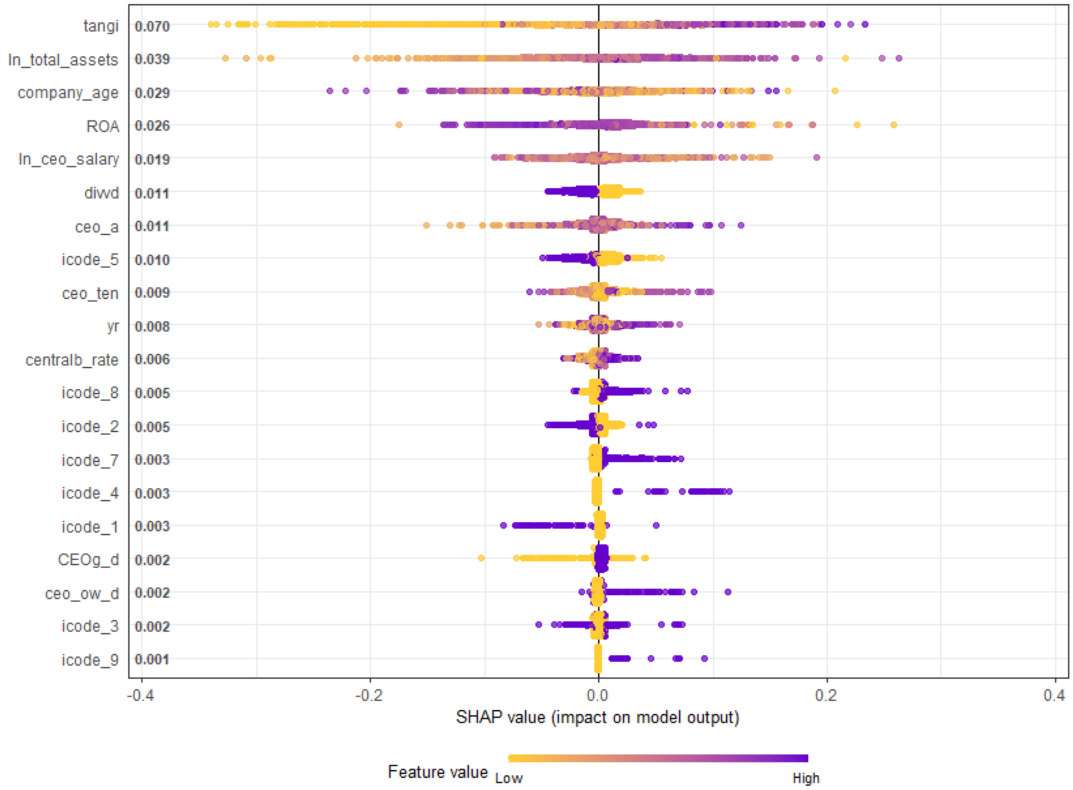
Table 7: Importance matrix from XGBoost

The table contains the most important predictors of leverage ranked by Gain from highest to lowest[40]. Cover and Frequency is also included. We added all variables available, as generally speaking, a higher number of variables is better for XGBoost. The added variables are Year and Central Bank rate. Year is what year the observation is in. The Central Bank rate is the average central bank rate that year. Industry Sector 1 to 9 are dummies for each sector, respectively. Industry sector 6 is financials and have been excluded.

Feature	**Gain**	**Cover**	**Frequency**	**Rank**
Tangibility	0.27	0.16	0.14	1
Size	0.16	0.18	0.15	2
Profitability	0.12	0.18	0.13	3
Firm Age	0.12	0.12	0.13	4
CEO Salary	0.09	0.15	0.11	5
CEO Age	0.05	0.08	0.07	6
Year	0.04	0.02	0.13	7
CEO Tenure	0.03	0.03	0.05	8
Central Bank Rate	0.01	0.01	0.03	9
Dividend	0.01	0.01	0.01	10
Industry Sector 5	0.01	0.01	0.01	11
CEO Gender	0.01	0.01	0.00	12
Industry Sector 8	0.01	0.00	0.01	13
Industry Sector 3	0.01	0.00	0.01	14
Industry Sector 7	0.01	0.00	0.00	15
Industry Sector 4	0.01	0.01	0.00	16
Industry Sector 2	0.01	0.01	0.01	17
CEO Ownership	0.01	0.01	0.00	18
Industry Sector 9	0.00	0.00	0.00	19
Industry Sector 1	0.00	0.01	0.00	20

[40] Note that the ordering changes if we rank by cover or frequency, but that the results are similar.

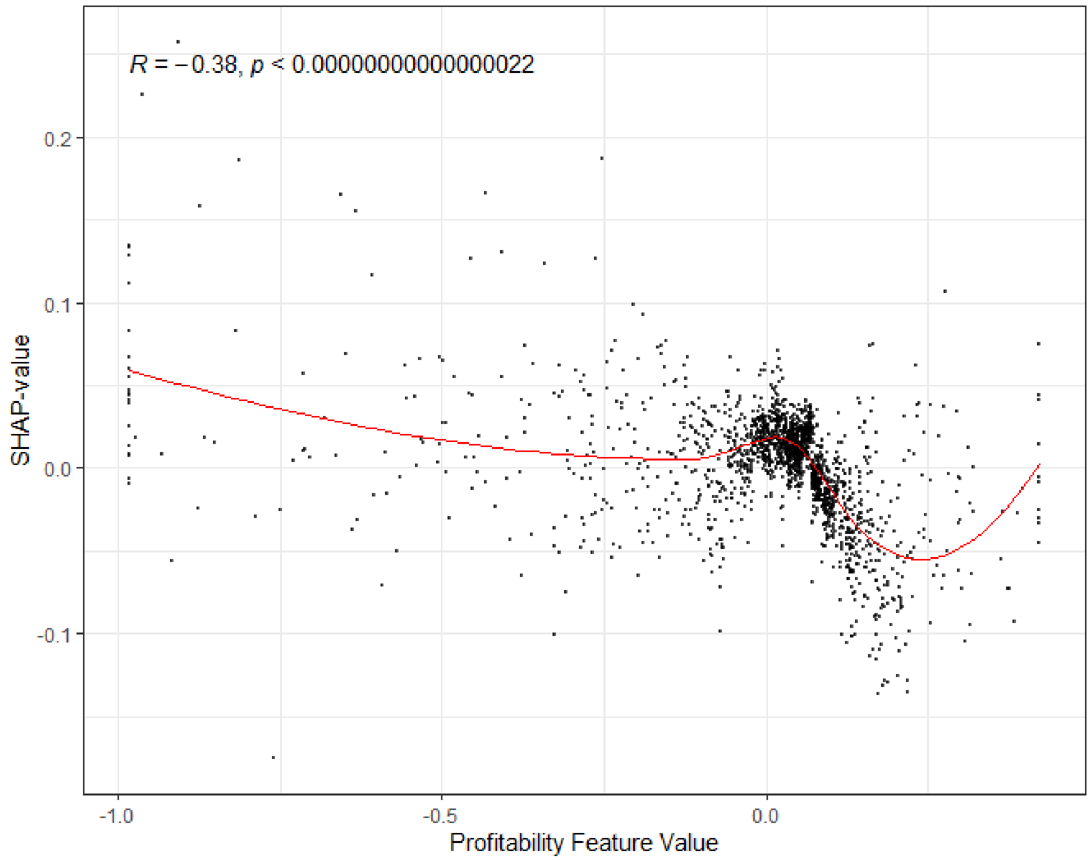
5.2.1 Bee Swarm and dependency plots



Plot 2: Bee Swarm plot of all independent variables and their importance
This plot provides feature importance ranked by SHAP-values. The plot shows every individual SHAP-value for each observation per independent variable. The color shows the variables real value from low to high, i.e., feature value. Dummy variables only have two values, 1 or 0 (Dividend for example), implying either dark yellow or dark purple. Firm age (company age in plot) shows values between 0 and 148, so the colored dots are more gradient.

Plot 2 shows the importance of all variables used for our boosted regressions trees. Again, showing a similar ranking to that of Gain, Cover and Frequency. We can see that the control variables are still the most important when predicting leverage, but that the CEO Salary and Age also are ranked highly.

The per observation SHAP-value is the increase in leverage that the observation marginally contributed. Having many dots to the left of SHAP=0 implies that on average that the variable/observation is responsible for decreasing leverage, i.e., tangibility. Having a low SHAP-value (being placed far to the left in the plot) while being dark yellow (a low variable-value) implies the observation is very positively correlated with leverage. While the bee Swarm plot also vaguely shows the distribution and non-linear relationships, it is hard to spot. We must look at dependency plots for more details. CEO Gender and CEO ownership dependency plots show a significant and positive correlation with the leverage ratio, which is similar to the regression results[41]. We also see that feature importance ranks Gender and Ownership very low. This is probably due to few females and CEOs with ownership in our sample, and we cannot draw conclusions.

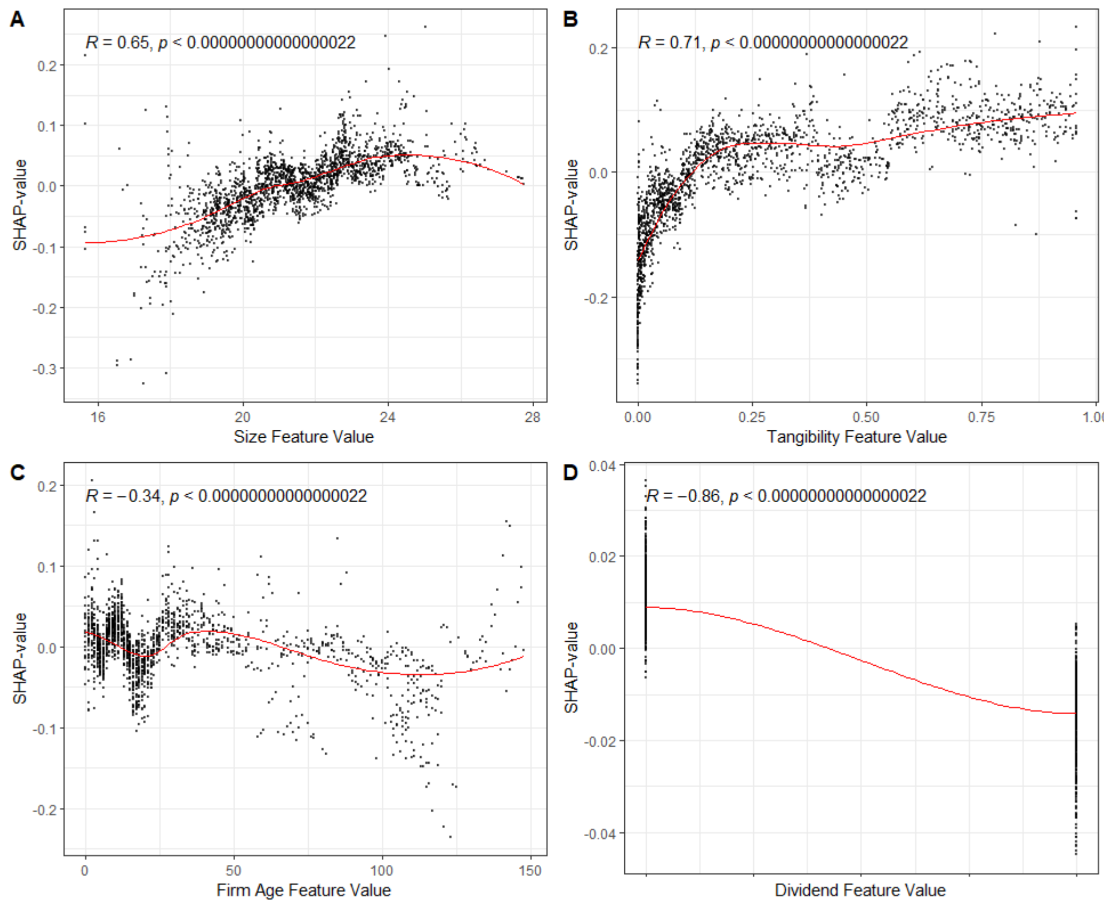


Plot 3: Dependency plot of Profitability on the x-axis versus its SHAP-values

We continue to plot dependency plots with the value (feature value) of the independent variable on the x-axis and its SHAP-value on the Y-axis. We use profitability as an example on how to interpret dependency plots. Plot 3 is the dependency plot for profitability. First, the correlation coefficient and its significance level posted in the left upper corner of the plot. Second, the red line represents a trend line and could be

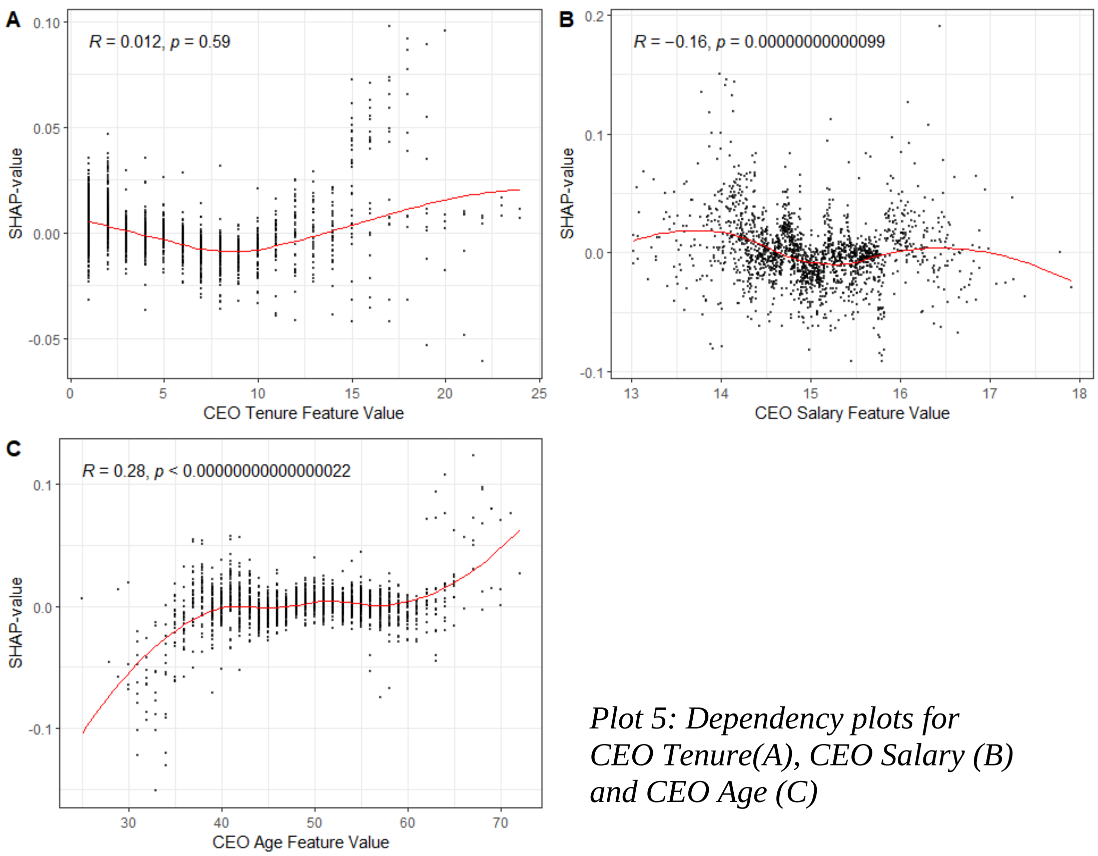
[41] We do not include these plots, as they provide little information other than correlation coefficient and significance of correlation. The software was not able to print trend-line due to few observations.

viewed as the average SHAP-value, or overall contribution towards leverage across all feature values. Third, we see that as Profitability goes above 0, and increases, it is linked with a decrease in leverage based on SHAP-values. We see when profitability is below 0, it has no particular effect on the leverage prediction. Profitability demonstrates that the software is able to show non-linear relationships.



Plot 4 shows the dependency plots for Size (A), Tangibility (B), Firm Age (C) and Dividend (D).

Plot 4 shows the remaining control variables. We briefly comment their effects on leverage. As size increases (plot 4A), so does leverage. Companies with less than LN(21) approximately in total assets are connected with a decrease in leverage, while bigger companies above LN(21) approximately, are connected with increases in leverage. Moreover, an increase in Size would, ceteris paribus, give higher leverage. Tangibility (plot 4B) also shows a linear connection to leverage, but unlike a linear regression we are able to see a plateu. The plot show that Tangibility less than 0.125 is connected to a decrease in leverage, while observations above 0.125 is connected with increases in leverage. Firm Age (Plot 4C) shows that the contribution towards leverage is about 0. Dividend paying companies are also confirmed to have lower leverage than companies who do not pay dividends (plot 4D).



Plot 5: Dependency plots for CEO Tenure(A), CEO Salary (B) and CEO Age (C)

CEO Tenure (plot 5A) have no impact on leverage, correlation between SHAP-value and CEO Tenure is not significant and very close to zero. Plot 5B, CEO salary does show a correlation of -0.16 which significant. The dependency plot for CEO Age, plot 5C, shows that CEOs' age is positively correlated, but it is possible to see that this is due to the few observations on each side. We therefore consider age as not having any effect on leverage.

5.3 Conclusive remarks on results across methodologies

The results from both the linear regression and XGBoost confirm that the control variables are the most important factors when determining leverage. Tangibility is found to be the most important variable in determining corporate leverage for firms in the sample, followed by size. Profitability is highly ranked in XGBoost but is not significant for the regression model. When it comes to CEO characteristics, we only consider CEO salary to have a relationship with leverage. It is the most important CEO characteristic in determining corporate leverage for both models. This could confirm the quiet life hypothesis, where it seems like CEOs that are paid more, are also having lower corporate leverage. However, we are not able to confirm that CEO Salary causes a lower leverage ratio. We do therefore confirm that we have a relationship in our data, but it is considered to only be a correlation. CEO Gender is found to have a significant effect at a 5% level when running the fixed effects models (not model 5D) and is somewhat confirmed by boosting. CEO Ownership is significant at a 10% level (model 1, 4, 5B and 5D), which is also to some degree confirmed by boosting. Both CEO Gender and CEO Ownership are ranked low by feature importance. We therefore conclude that CEO Salary is the only CEO characteristic with a relationship that consistently influence leverage ratio confirmed by fixed effects and XGBoost.

6 Conclusion

By using accounting data for the period 2000 to 2017 from the CCGR database we performed a study on the CEOs relationship to the corporate leverage in listed Norwegian companies. Our main research question was ”Does CEO Characteristics affect financial leverage?”. After running fixed industry effects and boosted trees, two methods which are placed at each extreme of the interpretability vs flexibility tradeoff, we were able to find the results to the 5 sub questions posted in chapter 4.1.

First, we asked, “How does tenure affect corporate leverage?”. We expected that CEOs with higher tenure, had lower leverage. We were able to find that the CEOs tenure does not influence the leverage ratio. The fact that the research is done on listed companies suggest that CEOs are more likely to be dedicated to life-long learning and training, this is considered to lower behavioral biases such as overconfidence or biased selfattribution[42] etc. A study conducted on private firms might suggest that tenure has an effect due to behavioral biases that come with the longer tenure that is not mitigated through training and learning.

Second, we asked, “Is the CEO living the quiet life?”. This refers to the salary of the CEO, and both models confirmed that there is some correlation between the CEO's salary and the leverage ratio. XGBoost ranks CEO salary as the most important CEO Characteristic, and in the linear regression CEO salary stays statistically significant through all models, except for model 2. Both linear regression and boosting gave the same result, a negative correlation with leverage. We are not able to confirm that CEO Salary causes a lower leverage ratio but considering the literature brought forward and the results found in our thesis we do conclude that CEO Salary and leverage ratio is correlated.

Third, we asked, “How does the ownership stake of the CEO affect the leverage ratio?”. We expected that the CEOs with ownership, has lower corporate leverage. Based on a very small sample of CEOs with ownership, we were able to attribute higher leverage in companies where the CEO has ownership via the regression models, opposite to what we expected. The sample size was not enough for XGBoost to give any meaningful results. We conclude that the results are inconclusive.

Fourth, we asked, “How does CEOs age impact corporate leverage?”. We expected that older leaders were more likely to have a lower leverage, but the effect was close to zero in our regression models. XGBoost did not show any relationship between CEO age and leverage ratio.

Fifth, we asked, “Does gender impact the corporate leverage?”. We expected that men were more likely to have a higher leverage. We found some evidence for this in the linear regression model, but with a small sample size it could be due to coincidence also. While gender stays statistically significant over almost all robustness checks in

[42] “Imputing positive outcomes to one’s own doing and imputing negative outcomes to external factors” (Goergen, 2018, 202)

the linear regressions, we were not able to confirm the results with XGBoost. The sample size of women, 93, was simply too small. We conclude that the results are inconclusive due to the lack of females in the sample.

In sum, we were not able to confirm that CEO characteristics are causing corporate leverage. We did however find that the CEO Salary had a negative correlation with the leverage ratio. We believe and conclude that the lack of relationship between leverage ratio and CEO characteristics is a sign of good corporate governance for Norwegian listed companies. With good corporate governance we argue that our results suggests that CEOs run the companies in the interest of shareholders, and not in their own self-interest. Our study suggest that other factors control the leverage ratio of a company, such as the owners, the board, the industry leverage or our mentioned control variables. We expect managerial biases to have a higher impact on leverage decisions for private firms due to poorer corporate governance.

This conclusion leads us to future research proposals. 1) Researching the same question as the thesis, but on privately held, small companies. These companies often have CEO duality, which increases the power of the CEO. This could give more clear results. 2) Replicating Cronqvist, Yonker and Makhija's study in Norway/Europe. Norway is very transparent with reported private wealth to the tax authorities and could make the study possible here. 3) The number of female CEOs is rising, and we expect the trend to continue in the following years. Doing the same study when the number of females on the exchange is higher, would make us more confident regarding the results.

7 Bibliography

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8 Appendices

8.1 Wordlist and definitions

Variable name in text	**Description and Calculations**
Firm ID	Unique company identifier. Norwegian Company Identification number.
Year	The accounting period/year of the reported variable.
Leverage Ratio	$$LR = \frac{Book\ Total\ Debt}{Book\ Total\ Assets} = \frac{D}{D+E}$$ The company's leverage ratio. Dependent variable of all models.
Profitability	$$ROA = \frac{EBI}{Book\ Total\ Assets}$$ Return on assets. Profitability measure. Control/independent variable.
Size	Book LN(Total Assets). Company size measure. Control/independent variable.
Tangibility	$$Tangibility = \frac{Book\ Tangible\ Assets}{Book\ Total\ Assets}$$ Measure of the company's tangibility. Control/independent variable.
Firm Age	The company age that year. Control/independent variable.
Dividend	Dividend dummy. 1 if company paid dividend that year, 0 if not. Control/independent variable.
Industry Sector	What industry the company belongs to. Ranging from 1 – 9. Classification variable. Control/independent variable.
Industry 1	Industry group "Agriculture, forestry, fishing, mining". Dummy variable. 1 for Industry Sector 1. 0 if not. Company classifier variable.
Industry 2	Industry group "Manufacturing, chemical products". Dummy variable. 1 for Industry Sector 2. 0 if not. Company classifier variable.

Industry 3	Industry group “Energy”. Dummy variable. 1 for Industry Sector 3. 0 if not. Company classifier variable.
Industry 4	Industry group “Construction”. Dummy variable. 1 for Industry Sector 4. 0 if not. Company classifier variable.
Industry 5	Industry group “Service”. Dummy variable. 1 for Industry Sector 5. 0 if not. Company classifier variable.
Industry 6	Industry group “Financial”. Dummy variable. 1 for Industry Sector 6. 0 if not. Company classifier variable.
Industry 7	Industry group “Trade”. Dummy variable. 1 for Industry Sector 7. 0 if not. Company classifier variable.
Industry 8	Industry group “Transport”. Dummy variable. 1 for Industry Sector 8. 0 if not. Company classifier variable.
Industry 9	Industry group “Multisector”. Dummy variable. Company included have multiple sectors. 1 for Industry Sector 9. 0 if not. Company classifier variable.
CEO Tenure	The CEOs tenure. (How long the CEO have worked in the current position)
CEO Salary	The natural logarithm of the CEOs compensation in the form of salary, stock options, bonuses, etc.
CEO Ownership	CEO ownership dummy. 1 if CEO has ownership in company. 0 if not.
CEO Age	The CEOs Age measured in years.
CEO Gender	CEO gender dummy. 1 if CEO is male. 0 if CEO is female.

8.2 Other tables

Table 8: Pooled Regression results

This table reports the coefficients and standard errors from 4 different pooled regressions with the Leverage Ratio as dependent variable and determinants of capital structure and CEO characteristics as independent variables. The sample consists of 303 Norwegian listed companies in the period 2000 to 2017. All variables are compiled from the CCGR database provided by BI Norwegian Business School in 2022. The financial sector has been excluded. The Leverage Ratio is defined as book total debt to book value of total assets. Profitability is the company's Return on Assets (ROA) and is defined as after-tax earnings before interest (EBI) to book value of total assets. Size is the natural logarithm of book total assets. Tangibility is defined as the ratio of book tangible assets to book total assets. Firm Age is the company's age measured in years. Dividend is a dummy equal to 1 if the company pays dividends, 0 otherwise. CEO Tenure is the time in years which the CEO has worked in that position. CEO Salary is the natural logarithm of the CEO's total salary, bonuses, options etc. CEO Ownership is a dummy equal to 1 if the CEO has ownership in the company, 0 otherwise. CEO is the CEO's age measured in years. CEO Gender is a dummy equal to 1 if male, and 0 otherwise. The standard errors are in parentheses and are Newey-West heteroskedasticity and autocorrelation robust standard errors. Significance levels are denoted by *, **, ***, which corresponds to 10%, 5%, and 1% levels, respectively.

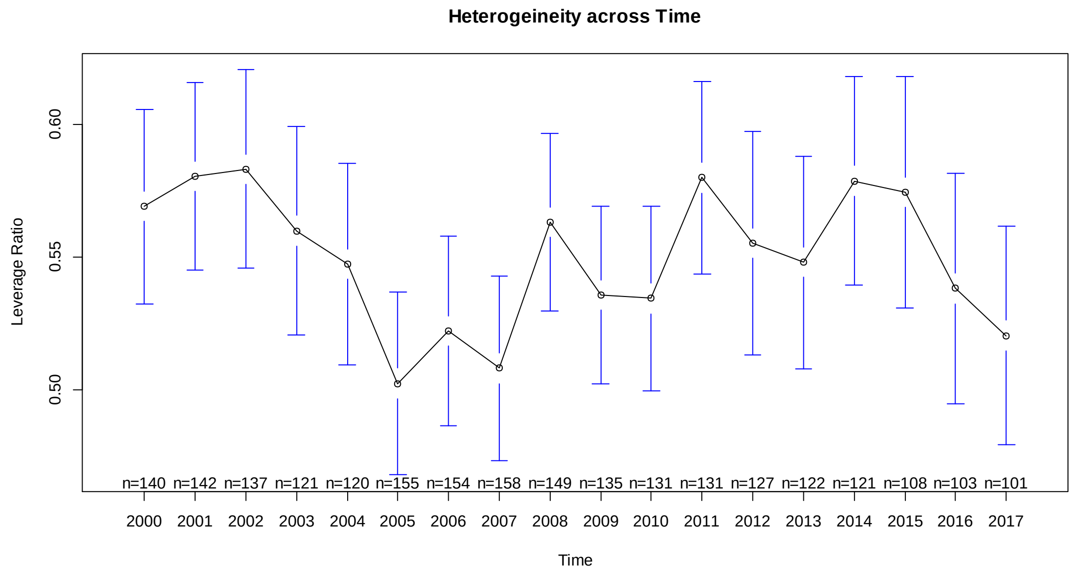
	(1)	(2)	(3)	(4)
Profitability	**-0.040**	**0.006**	**-0.036**	**-0.041**
	(0.035)	(0.036)	(0.035)	(0.035)
Size	**0.027*** **		**0.021*** **	**0.027*** **
	(0.004)		(0.003)	(0.004)
Tangibility	**0.237*** **	**0.292*** **	**0.248*** **	**0.239*** **
	(0.019)	(0.017)	(0.018)	(0.020)
Firm Age	**-0.0003** **	**-0.0001**	**-0.0003** **	**-0.0004*** **
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Dividend	**-0.051*** **	**-0.034*** **	**-0.048*** **	**-0.052*** **
	(0.009)	(0.009)	(0.009)	(0.009)
CEO Tenure	**-0.0004**	**-0.0004**		
	(0.001)	(0.009)		
CEO Salary	**-0.024*** **	**0.014** **		**-0.022*** **
	(0.008)	(0.006)		(0.008)
CEO Ownership	**0.049** **	**0.037**		**0.050** **
	(0.022)	(0.023)		(0.022)
CEO Age	**-0.00004**	**-0.0001**	**-0.0003**	
	(0.001)	(0.001)	(0.001)	
CEO Gender	**0.059** **	**0.052** **	**0.054** **	
	(0.026)	(0.025)	(0.025)	
Intercept	**0.231** **	**0.234** **	**0.024**	**0.263*** **
	(0.098)	(0.096)	(0.069)	(0.096)
Observations	**2355**	**2355**	**2355**	**2355**
R^2	**0.177**	**0.149**	**0.171**	**0.174**
Adjusted R^2	**0.174**	**0.146**	**0.169**	**0.172**

Table 9: Regression robustness results from pooled regressions

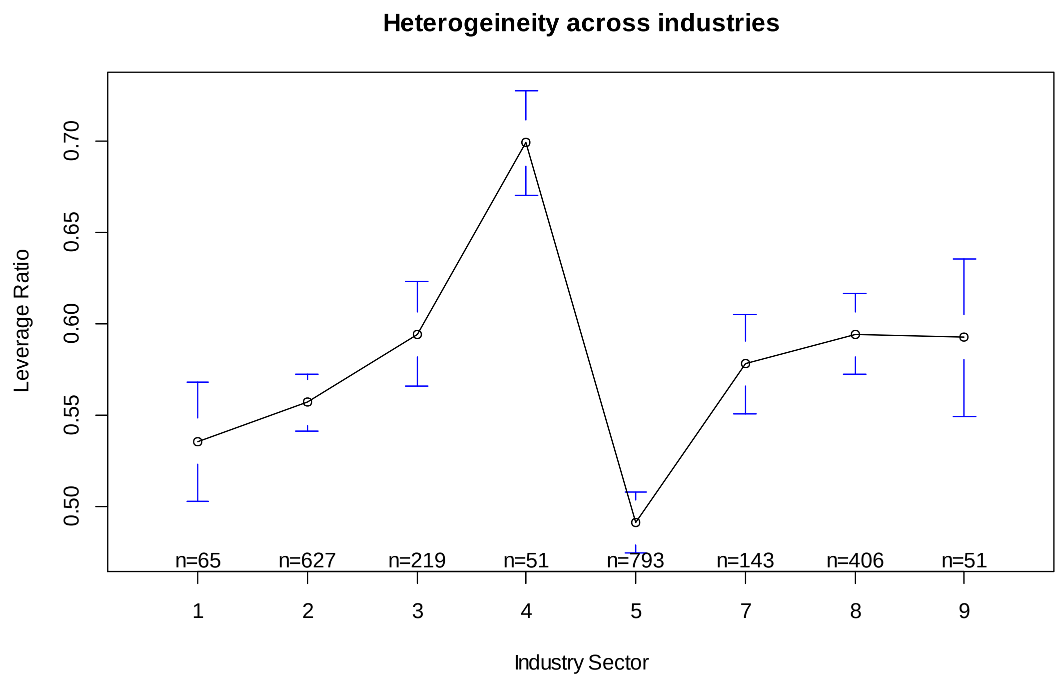
This table presents the same robustness checks as in table 5, but the models are pooled regressions instead. All variables are compiled from the CCGR database provided by BI Norwegian Business School in 2022. The Leverage Ratio is defined as book total debt to book value of total assets. Profitability is the company's Return on Assets (ROA) and is defined as after-tax earnings before interest (EBI) to book value of total assets. Size is the natural logarithm of book total assets. Tangibility is defined as the ratio of book tangible assets to book total assets. Firm Age is the company's age measured in years. Dividend is a dummy equal to 1 if the company pays dividends, 0 otherwise. CEO Tenure is the time in years which the CEO has worked in that position. CEO Salary is the natural logarithm of the CEO's total salary, bonuses, options etc. CEO Ownership is a dummy equal to 1 if the CEO has ownership in the company, 0 otherwise. CEO is the CEO's age measured in years. CEO Gender is a dummy equal to 1 if male, and 0 otherwise. The standard errors are in parentheses and are Newey-West heteroskedasticity and autocorrelation robust standard errors. Significance levels are denoted by *, **, ***, which corresponds to 10%, 5%, and 1% levels, respectively.

	POOLED (5a)	POOLED (5b)	5c) POOLED SUBSAMPLE	5d) POOLED LAGGED
Profitability	**-0.036**		**-0.034**	**-0.003**
	(0.024)		(0.033)	(0.040)
Size	**0.021*** **		**0.025*** **	**0.031*** **
	(0.002)		(0.004)	(0.005)
Tangibility	**0.249*** **		**0.243*** **	**0.198*** **
	(0.015)		(0.020)	(0.024)
Firm Age	**-0.0003*** **		**-0.001*** **	**-0.0004** **
	(0.0001)		(0.0002)	(0.0002)
Dividend	**-0.049*** **		**-0.055*** **	**-0.060*** **
	(0.009)		(0.012)	(0.011)
CEO Tenure		**-0.0002**	**0.0001**	**-0.0002**
		(0.001)	(0.001)	(0.0014)
CEO Salary		**-0.014** **	**-0.012**	**-0.030*** **
		(0.006)	(0.009)	(0.010)
CEO Ownership		**0.045** **	**0.043**	**0.057** **
		(0.022)	(0.036)	(0.028)
CEO Age		**0.00000**	**0.001**	**-0.001**
		(0.001)	(0.001)	(0.001)
CEO Gender		**0.053** **	**0.067** **	**0.053**
		(0.021)	(0.027)	(0.034)
Intercept	**0.062**	**0.161* **	**0.043**	**0.299** **
	(0.051)	(0.090)	(0.115)	(0.124)
Observations	**2355**	**2355**	**1491**	**2031**
R^2	**0.169**	**0.008**	**0.186**	**0.162**
Adjusted R^2	**0.167**	**0.006**	**0.181**	**0.158**

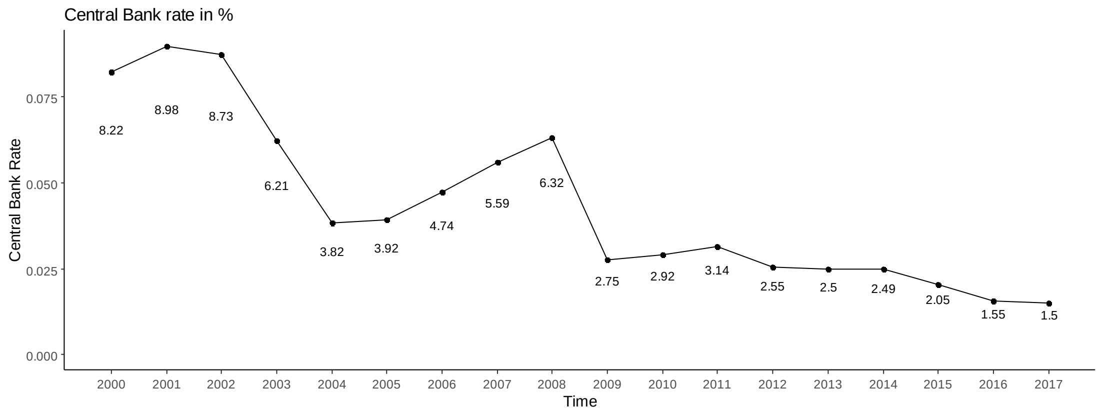
8.3 Other plots



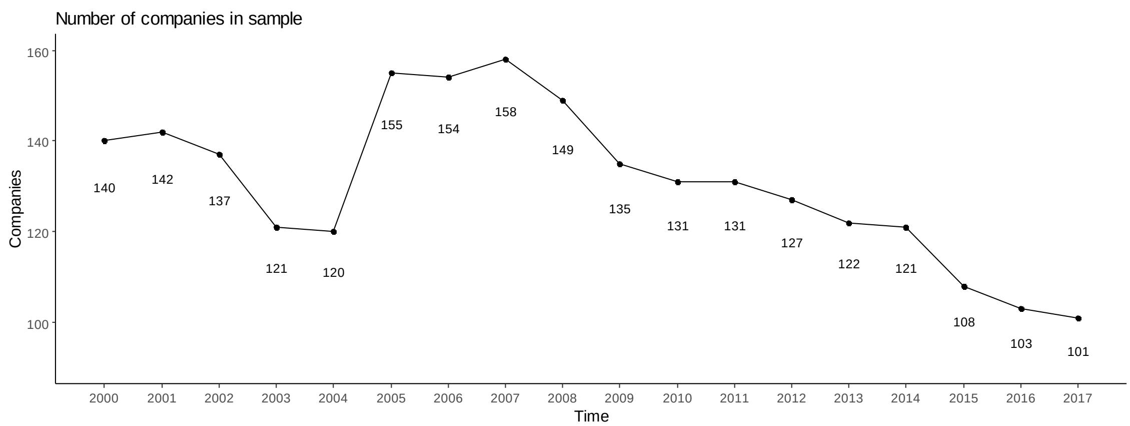
Plot 6: Heterogeneity across time. n = observations pr year. Blue lines show 95% confidence interval, upper and lower.



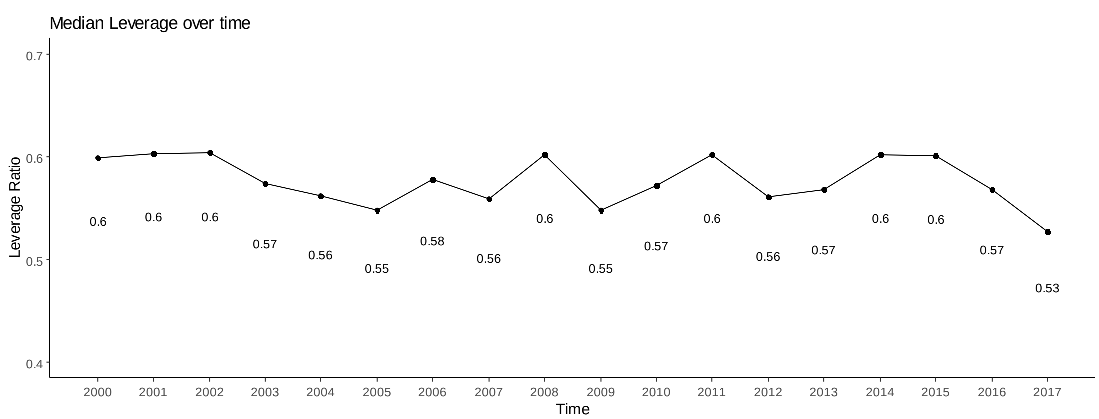
Plot 7: Heterogeneity across industries. n = Observations in sector. Blue lines show 95% confidence interval, upper and lower.



Plot 8: Central Bank Rate development in %.



Plot 9: Number of companies in sample through time.



Plot 10: Median Leverage over time across all industries.