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What Are, If Any, the Explanatory Financial Factors of Bankruptcy in Norwegian Startups?

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Abstract

In this paper, we investigate startups that have survived the first crucial years, but which then went bankrupt during the following years. The intention behind this focus is to acknowledge why some startups do not cross the chasm.

A logistic regression model was designed with several variables to explain bankruptcy. The usage of the Akaike Information Criterion (AIC) was central to narrow down relevant variables alongside significance and z-statistics. Robustness has also been tested for the explanatory variables. In general, one could say that since the solvency ratios were the most dominant explanatory factors, which indicate how Norwegian startups have a negative net worth and a non-manageable debt level. Since Norwegian startups hold less liquid assets, one important issue is the amount of untapped cash within the organization. The industries that experienced bankruptcy the most were (i) water supply; sewerage, waste management, and remediation activities, (ii) construction, (iii) transportation and storage, and (iv) accommodation and food service activities. One thing these industries have in common is the number of tangible assets. As a result, the tangible assets could be more difficult to quickly transform into cash.

Interaction effects have not been considered, nor dynamic effects or firm fixed effects. The variables that have been tested have previously been tested on public and listed companies, and not on startups. The findings could be used to greater understand the financial struggles Norwegian startups have. The different actors that could find the findings useful are angel investors, venture capitalists, the authorities, and most important the entrepreneur and the Norwegian startup environment.

The concept of bankrupt startups often concerns aspects connected to the entrepreneur and not necessarily underlying financial reasons. Therefore, this master thesis could contribute to filling an important knowledge gap within the research field.

Keywords: Startups, financial explanatory factors, Norway, financial ratios, bankruptcy, financial statement analysis, capital structure, AIC, logistic regression.

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Introduction

The concept of bankrupt startups often concerns aspects connected to the entrepreneur and not necessarily latent financial reasons.[1] The idea stems from how intra- and interpersonal aspects to a greater extent influence whether the startup goes bankrupt.

Whilst this aspect was confirmed through various previous research (Brüderl, Preisendörfer, and Ziegler, 1992; Cressy, 1996; Cantamessa, Gatteschi, Perboli, and Rosano, 2018), it still leaves a central question in regards to bankruptcy research connected to startups: What are the possible financial reasons for why startups fail? Research on corporate finance is nearly exclusively on listed organizations. The most noticeable justification for this imbalance, according to Berzins and Bøhren (2009), is the lack of financial data on unlisted companies, particularly in the United States. In Norway, however, Berzins and Bøhren (2009) emphasized how the data availability and quality roughly coincide with both unlisted and listed organizations. These arguments open for corporate finance research on startups that could be burdensome to accomplish in other countries due to lack of available data. Therefore, research possibilities arise on financial explanatory factors for why Norwegian startups fail. In this thesis we study:

What are, if any, the explanatory financial factors of bankruptcy in Norwegian startups?

In this paper, we investigate startups that have survived the first crucial years, but which then went bankrupt during the following years. The intention behind this focus is to acknowledge why some startups manage to cross the chasm, whilst others do not. Statistics Norway (2019) considers an organization

[1] Research by for instance Brüderl, Preisendörfer, and Ziegler (1992) and Cressy (1996) recognized how approaches on why startups fail mostly focus on aspects connected to the entrepreneur, and due to financial reasons. Cressy (1996) found human capital to be the most accurate factor to explain the failure, based on conducted studies in the UK. In addition, Cantamessa, Gatteschi, Perboli, and Rosano (2018) found business development plans as an explanatory factor of failure. Further reasons and elaborations will be highlighted in the literature review.

with operating years from one to five years as a startup, whilst Skatteetaten (2020) consider a startup for up to 6 years.[2] For this master thesis, the age of the startup is considered up until 6 years to get a larger sample.

The aim with this thesis is to recognize financial explanatory factors based on bankruptcy indicators from the financial statement for all Norwegian startups to acknowledge common denominators for bankruptcy. Since the first operating years may not reflect the true financial explanatory factors of bankruptcy, and to a greater extent explain other latents reasons, the bankrupt startups that failed between the years three to six are examined. The different potential causes for an immediate bankruptcy could display non-existent product demand, administrative problems, and so forth. For the bankrupt startups, the financial statements for all years in business is taken into consideration up until the year of bankruptcy. Thus, for non-bankrupt startups, the financial statements for all first six years in business is taken into consideration. Within this paper, the term failure is defined as bankruptcy due to forcible dissolvement. By defining failure as bankruptcy, it opens for the use of high-quality data from the Centre for Corporate Governance Research (CCGR) which strengthens the quality of the study and ability to answer the research question.[3]

In 2018, NOK 2.5 billion was invested in venture capital in Norway, mainly affiliated with investments in startups (DNB, 2020). Statistics Norway (2019) point out how 29.8 percent of startups are still active after five years of operations. Even though a considerable amount of capital is invested in startups, Bammens and Collewaert (2014) notes how, for instance, angel investors often strongly rely on trust and how trust influences the evaluation of the portfolio company performance. Hence, one could argue that there is great uncertainty connected to what financial factors to evaluate for investment purposes in startups. Angel investors are often, according to Drover, Busenitz, Matusik,

[2] Skatteetaten (2020) defines a startup through several measures: age, employees, balance sheet amount, annual salary basis, and requirement of no passive capital management. This thesis measures startup through age, so only age is retrieved from Skatteetaten's (2020) considerations.
[3] CCGR is a research centre connected to BI Norwegian Business School, and was established in 2005. The database collects various information on both listed and non-listed companies in Norway. Moreover, CCGR is financed through contributions from BI, the Research Council of Norway, as well as the business community.

Townsend, Anglin, & Dushnitsky (2017), influential or wealthy people who contribute with capital to startups that incite development and innovation, usually in exchange for shares or convertible debt.

DNB (2020) acknowledges how startups are essential to transform and contribute to the Norwegian business environment, especially the establishment of new jobs. One could argue how one of the substantial advantages of startup communities, like Silicon Valley, is the culture of sharing experiences that one often learns the hard way. Entrepreneurs who are restricted to participate in a knowledge-sharing environment due to several reasons such as location, network, and exclusivity, could need to lean on other informational sources than the startup environment. Thus, these aspects highlight the importance of bankruptcy research in the startup environment.

Næringslivets Hovedorganisasjon (2020) reports how small and medium-sized enterprises (SMEs) constitute more than 99 percent of all businesses in Norway, and how 47 percent of the workforce in the private sector is working in an SME. The definition of an SME in this thesis follows the European guidelines set by the European Commission (2015), which concerns the number of employees, total annual balance sheet, as well as annual turnover. Concretely, the European Commission (2015) requires an SME to have less than 250 employees, the total annual balance sheet amount to not exceed EUR 43 million, and have a yearly turnover below EUR 50 million. The value creation by SMEs in 2017 in Norway amounted to NOK 700 billion, according to Næringslivets Hovedorganisasjon (2020). Within the SME segment, most of the startups could be located through either only the early years or their whole operating period. In addition, it is essential to highlight how several Norwegian SMEs, as well as larger companies, have previously been a startup and managed to scale up. As such, successful startups can be said to have an extensive effect on the Norwegian economic environment.

In light of the presented arguments, this thesis will be of considerable interest. First, startup research mostly focuses on aspects connected to the entrepreneur, where there is a limited amount of financial explanatory reasons for why startups go bankrupt (Brüderl, Preisendörfer, and Ziegler, 1992; Cressy, 1996; Cantamessa, Gatteschi, Perboli, and Rosano, 2018). Second, every year several startups file for bankruptcy, where the findings could contribute to greater knowledge on potential warning signals. Lastly, this research opens for new angles on startup bankruptcy research, which could spark research interest.

In our thesis we find that the solvency ratios were the most dominant explanatory factors, which indicate how Norwegian startups have a negative net worth and a non-manageable debt level. Since Norwegian startups hold less liquid assets, one important issue is the amount of untapped cash within the organization. This untapped cash potential could be used to manage the debt level. The industries that experienced bankruptcy the most were (i) water supply; sewerage, waste management, and remediation activities, (ii) construction, (iii) transportation and storage, and (iv) accommodation and food service activities. One thing these industries have in common is the amount of tangible assets. Therefore, it could be more difficult to quickly transform the assets into cash.

The thesis will be structured into different sections. The first section will review relevant literature for the study. Afterward, the data collection method, as well as research methodology, will be explained. In this section, a model will be proposed on how to explain bankruptcy using financial ratios on Norwegian startups. However, it is important to note that no theories of bankruptcy or usefulness of financial ratios are tested in this thesis. Thereafter, the results will be presented and analyzed. Lastly, some concluding remarks will be made together with possible limitations and directions for future research.

Literature Review

This literature review will present different approaches on both the startup and bankruptcy prediction topics, as well as the various methods practiced. As a result, for this thesis a quantitative method with a statistical approach was used, which will influence the literature review. This literature review will seek to display the gap between bankruptcy prediction using financial ratios and startups, showing how bankruptcy prediction research concerns organizations in general, and not exclusively startups. Since startups are considered an important contribution to the business environment, the contribution to the research field with knowledge on sensitive variables for startups is valuable.

The Different Approaches on Bankruptcy Research

Research on bankruptcy prediction with the help of ratios originates back to the 1930s. Since then, numerous research projects have been conducted on most appropriate statistical methods to predict bankruptcy. From the 1930s until the middle of the 1960s, single factor ratio analysis, commonly termed univariate analysis, was the most used method. Beaver (1966) was central within the univariate analysis and discovered several signs of bankruptcy five years before the bankruptcy. However, this changed when Altman (1968) and Ohlson (1980) released their respective studies.

Although both Altman (1968) and Ohlson (1980) used statistical methods to predict bankruptcy, the two studies had distinctive differences. One difference concerned how Altman (1968) used a multiple discriminant model (MDA) that analyzed combinations of ratios to remove possible misclassifications and ambiguities. The model resulted in a Z-score formula which predicted bankruptcy with 72 percent accuracy two years before the failure would occur. On the other hand, Ohlson (1980) used conditional logit analysis to avoid the commonly known problems with the MDA, and created the O-score as a substitute for the use of Altman's Z-score. Besides, Ohlson (1980) meant that ratios that targeted the balance sheet were the most advantageous. Another difference between Ohlson's O-score and Altman's Z-score was how Ohlson (1980) included a country-specific parameter that opened for measurements of economic, social, and cultural factors, whilst Altman's Z-score had no similar element. Despite their differences, the statistical models presented by Altman (1968) and Ohlson (1980) are both adopted today as proxies for financial distress in consonance with Kensinger (2010).

What statistical method the most appropriate for bankruptcy prediction was debated among researchers. The following four methods were found by Collins and Green (1982) through an examination of published research as the most common: the multiple discriminant analysis (MDA), the linear probability model (LPM), the quadratic discriminant analysis (QDA), and the logistic regression (LOGIT). Laitinen and Laitinen (2000) agreed to some extent with Collins and Green (1982) but concluded with the linear discriminant analysis and logistic regression analysis as the most popular forms. However, Collins and Green (1982) argued that the logit model was the most successful due to the lowest amount of type one errors. On the other hand, Li, Lee, Zhou, & Sun (2011) argued that a combination of a binary logit model and a combined random subspace could have been beneficial. Mostly since this combination presented by Li, Lee, Zhou, & Sun (2011) considered opinions of different decision-makers, which resulted in improvement of the logit model. Also, Jones and Hensher (2004) noted that a mixed logit model was preferred over multinomial logit models (MNL) and binary logit. This was due to how Jones and Hensher (2004) included fixed parameters as well as improvement like heterogeneity in the means. But, Campbell, Hilscher, and Szilagyi (2008) argued the logit model should be dynamic to include both the short and long perspective, as well as variables based on both accounting and market measures.

Pompe and Bilderbeek (2005), Mayo and Rosenbloom (1975), and Jackendoff (1962) recognized how ratios were advantageous within bankruptcy research. Pompe and Bilderbeek (2005) exhibited how approximately all ratios had some predictive power. Therefore, a dichotomous classification test was shown by Pompe and Bilderbeek (2005) to not have given very high results of the univariate and multivariate importance of ratio stability. Thus, the study by Pompe and Bilderbeek (2005) highlighted how the prediction of bankruptcy was detectable in close to all aspects of a firm's financial position. Besides, Mayo and Rosenbloom (1975) agreed with Pompe and Bilderbeek (2005), and acknowledged the benefits of ratio analysis since this method of analysis allowed the researcher to recognize the weakest firm within the sample. However, Jackendoff (1962) agreed with Bellovary, Giacomino, and Akers (2007) on how profitable firms had a greater net working capital to total assets and current ratio. In addition, the debt to worth ratios displayed greater effects for unprofitable companies in the study by Jackendoff (1962). On the other hand, Lensberg, Eilifsen, McKee (2006) argued how non-financial ratios could have been beneficial to include to reflect financial distress, size, fraud indications, as well as the auditor’s opinion. Not only, but reduction of potential measurement error was argued by Morris (1997) as achievable through including the latent risk variables in virtue of accounting ratios and identification of financial distress.

Nevertheless, Dakovic, Czado, and Berg (2007), Laitinen and Laitinen (2000) Ohlson (1980), Altman, Iwanicz-Drozsowska, Laitinen, and Suvas (2016) agreed that there were measures to take to improve the prediction performance. As reported by Dakovic, Czado, and Berg (2007), there was an essential relationship between the probability of bankruptcy and explanatory variables. However, Laitinen and Laitinen (2000) believed the key was to involve explanatory variables through an interaction term. In addition, the importance of the country-specific parameter to distinguish between national underlying differences was observed in the study by Ohlson (1980). This country-specific parameter would, in agreement with Altman, Iwanicz-Drozsowska, Laitinen, and Suvas (2016), have enhanced classification accuracy. Nevertheless, Altman (1968) believed in a more simplistic nature with a focus on information retrieved from the financial statement.

Bernhardsen (2001) agreed to some extent with Altman, Fargher, & Kalotay (2011) on different aspects to include in the model. Bernhardsen (2001) argued for variables that concerned liquidity, profitability, solidity, age, size, and industry characteristics, based on the findings in previous literature (Altman, 1968; Ohlson, 1980; Laitinen & Laitinen, 2000) . However, equity prices, firm characteristics, accounting measures as well as distress conditions based on industry-level anticipations were noted by Altman, Fargher, & Kalotay (2011) as essential. But, the aspects by Bernhardsen (2001) built the foundation for the articles by Eklund, Larsen, and Bernhardsen (2001) and Bernhardsen and Larsen (2007) which was used by the central bank of Norway to predict the likelihood for bankruptcy in Norwegian limited companies, also known as the SEBRA model.[4] These adjustments found in Eklund, Larsen, and Bernhardsen (2001) and Bernhardsen and Larsen (2007) corresponds with Bellovary, Giacomino and Akers (2007) findings on how newer bankruptcy models and studies had added complexity to the prediction model with both additional and new variables.

The different approaches to bankruptcy research strongly build on one another's models. It was repetitive how the main aim was to explain how one another's models could be improved, or how past limitations could have been solved through minor adjustments. The research purpose was often the same, which was to create the best possible model and explanatory factors to explain bankruptcy.

The Nature of Startup Research

Both Cassar (2004) and Watson and Everett (1996) acknowledged how startups financed themselves often depended on whether the resource was a tangible or intangible asset. However, Cassar (2004) observed how tangible assets often were financed through formal financing opportunities, whilst intangible assets strongly relied on less formal financing such as loans from individuals. Besides, creditors found startups with tangible assets generally more appealing in bankruptcy circumstances, as reported by Watson and Everett (1996), than startups with intangible assets. Furthermore, the research by Cassar (2004) found that the size

[4] The SEBRA model was adjusted by Bernhardsen and Larsen (2007) and presented both an extension of the original model in addition to a more basic version. The result of the adjustment gave greater accuracy and suitability. The SEBRA model presented by Bernhardsen and Larsen (2007) is the one Norges Bank uses today.

of the startups was strongly correlated with the proportion of debt (both short and long-term) and the number of external bank funds. Thus, these findings by Cassar (2004) corresponded with theories within treasury management on how the growth of a firm influenced the use of more sophisticated financial instruments.[5]

Karels and Prakash (1987), Bellovary, Giacomino and Akers (2007), and Fredland and Morris (1976) saw how the research literature on both startups and bankruptcy had various definitions for the term failure. Failure was acknowledged by Karels and Prakash (1987) to consist of a wide array of definitions, especially in studies connected to prediction. Besides, Bellovary, Giacomino, and Akers (2007) noticed how the definition of failure varied from the shortcoming of payments related to financial obligations or difficulties connected to financial stress, to concrete filing for liquidation or bankruptcy. From an economic perspective noted by Fredland and Morris (1976), failure was any rate of return on investment smaller than the opportunity cost that the organization faced. On the other hand, some studies did not define failure to any extent. The different applications of the term failure lead to how Cohran (1981, p. 51) argued:

> One reason for confusion on small business failure rates is the multitude of contending definitions and measures of the several concepts. Small business has been defined by a bewildering number of criteria. Total worth, relative size within industry, number of employees, value of products, annual sales or receipts, net worth, or a combination of any of these characteristics could serve as a basis for classifying firms according to size.

Brüderl, Preisendörfer, and Ziegler (1992), Cressy (1996), Cassar (2004), and Cantamessa, Gatteschi, Perboli, and Rosano (2018) were divided on the underlying reason for why startups fail. The fundamental reasons spanned from factors affiliated with the entrepreneur to solely financial reasons. Several

[5] Treasury Management: A Practitioner's Perspective by Steven Bragg acknowledged the practical aspects of treasury management. Treasury management has a wide range of tasks, where Bragg separates cash management, financing, risk management, and treasury systems. Theories presented in Bragg's book explain how the age of the company influences the use of sophisticated financial instruments.

organizational characteristics and strategies were noted by Brüderl, Preisendörfer, and Ziegler (1992) as the most crucial determinants of survival for businesses. The amount of capital invested and strategies concerning which market to target were pointed out by Brüderl, Preisendörfer, and Ziegler (1992) as some of the most central explanatory factors. But, the organization type was found by Cassar (2004) to not have explained the amount of leverage within the organization.

However, Cressy (1996) did a study in the UK and found that human capital was the most accurate factor to explain the failure. With human capital, Cressy (1996) meant qualifications, skills, and knowledge amongst the employees. Therefore, human capital among employees was not adequate for the startup to survive. The interrelationship between financial capital and survival was also found to be counterfeit by Cressy (1996). In contrast, Cantamessa, Gatteschi, Perboli, and Rosano (2018) found a failure pattern for startups connected to how the business development plans arise. The authors recognized that the entrepreneur often focuses solely on the product, and not on how to properly prosper the business.

Ruback (1984), Fredland and Morris (1976), Cassar (2004), White (1983), and Watson and Everett (1996) suggested different costs related to the failure aspect. The cost was pointed out by Fredland and Morris (1976) to be re-distributional and not necessarily an economic cost. Besides, Ruback (1984) noted that the loss of human capital and doubt among customers and suppliers had a greater cost than the direct cost of bankruptcy. Moreover, indirect costs related to the failure were noticed by Ruback (1984) to be more difficult to measure. Also, Fredland and Morris (1976) noted that seniority often decided whether one was prioritized when resources were distributed. The seniority within bankruptcy instances for startups was found in Cochran’s (1981) study to have been influenced by both private and public organizations which interacted with startups.

The aspect by Fredland and Morris (1976) harmonized with Cassar (2004), where Cassar (2004) noticed that startups early on concentrated on how to build a beneficial relationship with credit institutions. Creditors were found by Watson and Everett (1996) to often have evaluated the number of tangible assets and other resources in case of possible bankruptcy matters and respective costs. Besides, bankruptcy costs were acknowledged in White's (1983) study to have concerned both ex-ante and ex-post-bankruptcy. Therefore, White (1983) noted how bankruptcy costs could have included latent costs related to a possible attempt to save the organization.

Data

Collection & Filtration of Data

The data for this quantitative and descriptive thesis is retrieved from the Centre for Corporate Governance Research (CCGR) database, which is a research centre connected to BI Norwegian Business School. The database collects various information on both listed and non-listed companies in Norway, for instance, financial statements and corporate governance data. Therefore, the CCGR database contains important and detailed information that gives valuable insight into Norwegian startups, where public information is usually very limited.

The secondary, archival data retrieved from CCGR for this thesis is extensive with information on Norwegian organizations from 2000 to 2017. The retrieved variables for this research resulted in unbalanced panel data of 4 171 441 observations. However, the database went further back than year 2000, if only accounting information were used. The starting point of the data in this thesis was 2000, since this was the first year with reported data on corporate governance. Afterwards, several steps were made in order to filter the data for the research purpose.

First, in accordance with Frank and Goyal (2009) and Berzins, Bøhren and Stacescu (2012), financial firms, public firms and utilities were dropped. This was due to especially financial firms' different accounting practices and capital requirements. Second, the same practice as Bøhren and Berzins (2009) were applied in regards to removing passive organizations within the sample. Passive organizations were organizations with no assets, no total revenue, no total operating revenue, or no employees. However, only observations with no assets or no revenue were removed, since startups may not have registered employees.

Third, observations with inconsistent accounting data within the sample were dropped. Garcia de Olalla López (2014) described such observations where there were negative total current liabilities, negative total current assets, negative total fixed assets, and negative liabilities to financial institutions. Fourth, independence based on ultimate ownership was considered, so organizations that were non-independent were dropped. This measure was taken to minimize the amount of possible holding companies within the sample.[6] This step also minimized the amount of possible organizations that had the main purpose of transferring wealth, in addition to joint ventures.

Fifth, the thesis' definition of a startup was used in order to detect possible startups in the dataset. Since startups were defined with help of operating years, the relevant startups were detected through: (i) subtracting the foundation date from date of forcibly dissolvement to find the operating days, and (ii) subsequently divided with 365 to recognize operating years. Leap years were not considered since there would be no significant effect on the calculations. The focus of the thesis was to investigate startups that had survived the first crucial years, but which then went bankrupt during the following years. Hence, all observations that had operating years below three years and operating years longer than six years were dropped.

Sixth, a number of bankrupt startups were retrieved through the date for forcible dissolvement. Therefore, a dummy variable was generated that took the value of one if the startup were bankrupt, and 0 if non-bankrupt. Hence, startups which did not have such a date recorded and still operated in 2017 were considered non-bankrupt.[7] Data on non-bankrupt startups was necessary for the

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[6] Holding companies are here referred to as the companies investors usually create for investment and ownership purposes.

[7] There are mainly three forms of forcibly dissolvement in Norway: (1) insolvency (konkurs), (2) compulsory liquidated (tvangsavviklet), and (3) compulsory dissolved (tvangsoppløst) (Konkursrådet, 2011). Since the focus of the thesis was the explanatory financial factors of bankruptcy in Norwegian startups, data on forcibly dissolvement due to insolvency was collected and analyzed.

logistic regression model to function properly. Observations were dropped for the non-bankrupt startups that had operated for more than six years, since only the organizations that would be categorized as a startup were to be included.

Lastly, organizations that operated within more than one industry were dropped. This measure could be argued to be somehow controversial, but through a focus on "one industry organizations" it was easier to sort the industries as well as created the possibility of proper overview of which industries that struggled the most. In addition, eight industries were dropped based on the latent characteristics. These industries reflected financial firms (different accounting policies), industries with no bankruptcies, and industries with few observations such as the mining industry, electricity and gas, other service activities, and unknown industries.

After the selection strategy was applied, the relevant unbalanced panel data for startups was 537,590 observations in the period from 2000-2017. From these 537,590 observations, 3,900 of these constituted the startups that have been forcibly dissolved.

Variables

The proposed binary logit model consisted of both a set of control and explanatory variables. As earlier mentioned, whether the startup went bankrupt was based on the date of forcibly dissolvement due to insolvency. Therefore, the proposed model aimed to describe the latent financial explanatory factors behind the bankruptcy. Appendix 1 summarizes the characteristics of the explanatory and control variables proposed in the binary logit model. When the control variables were selected, both Frank and Goyal (2009)[8] and Rajan and Zingales' (1995)[9] factors were taken into consideration. Even though Frank and Goyal (2009) and Rajan and Zingales (1995) study leverage and capital structure, their research was relevant since capital structure influences the combination of debt and equity which is central within bankruptcy. Debt and equity are central within bankruptcy

[8] Frank and Goyal (2009) acknowledge how the market leverage had six core factors: tangibility, industry median leverage, firm size, profit, expected inflation, and the market-to-book assets ratio.
[9] According to Rajan and Zingales (1995) the following four variables are central when deciding on control variables: profit, sales, market-to-book, and tangibility.

since these factors influence daily operations and growth. Since startups were seldom listed or public early on, a definition of leverage that was book-based was applied. Also, most of the startups were anonymous within the dataset, so there would be difficulties to recognize market-based information if there were listed or public startups. Therefore, variables such as market-to-book and expected inflation were not considered.

A dummy variable that reflected bankruptcy was made. The variable took the value 0 if non-bankrupt and 1 if the startups went bankrupt. Hence, a new bankruptcy variable *bankrupt2* considered the time aspect to reflect the non-bankrupt years through the value of 0 along with the non-bankrupt startups, and 1 in the year of bankruptcy.

CEO gender and age were variables that reflected possible risk aversion. Harris and Jenkins (2006) found that women often had lower risk appetite than men, which was argued to justify lower profitability for companies with female leaders. Both He, Inman and Mittal (2008) and Demartini (2008) noted how the dissimilar risk appetite resulted in a stronger orientation for female entrepreneurs and their decision making towards a lower and different position on the risk-return curve. A common understanding in finance is the relationship between high risk and high reward, but also the greater possibility of failure. Therefore, CEO gender, *FEMALECEO*, and CEO age, *CEOA*, were both measured in the logistic regression model. *FEMALECEO* is a binary variable that is 1 if female CEO, and 0 if male CEO for observation i at time t.

Frank and Goyal (2009) pointed out how the nature of assets influenced capital structure and leverage. How startups financed themselves mostly depended on whether the assets were intangible or tangible, according to Watson and Everett (1996) and Cassar (2004). Whether the assets were of high or low-risk were influenced by tangibility. Since tangible assets bind capital to a greater extent through inventory compared to intangibles, it would affect the inventory turnover. Moreover, the inventory turnover influenced the generation of cash, which lastly affected the possibility of bankruptcy. Watson and Everett (1996) noted how investors also evaluate the number of tangible assets when an investment is made in case of potential bankruptcy since tangible assets hold cash.

Also, Frank and Goyal (2009) found a positive connection between leverage and tangibility, as a result of minor debt-related agency problems and reduced anticipated costs of distress. However, pecking order theory recognized how organizations with higher tangibility had lower leverage ratios. [10] In alignment with the aspects from the pecking order theory, Frank and Goyal (2009) found tangibility as a proxy in consideration of diverse economic forces. Therefore, the potential influence of the nature of assets was determined through tangibility, *ITTA*, for observation *i* at time *t* in this study.

Bernhardsen (2001) explained how it was beneficial to include the organization's age since age would reflect how the organization would need time to develop a functional organizational structure and management skills. Also, Bernhardsen (2001) emphasized how young companies could experience uncertainty connected to actual production costs, which could lead to a riskier business. A more precarious business could lead to a higher probability of bankruptcy. Lukason and Camacho-Miñano (2019) acknowledged firm age as a control variable and noticed how older organizations were less profitable and liquid. Besides, this variable reflected what organizational age that had an essential role in a potential bankruptcy. Therefore, the organization's age was measured through subtracting the year of observation with the founding year, *i.AGE,* for observation *i* at time *t*. Even though *i.AGE* is not a financial factor, it is included as a control variable to help describe in what operating year Norwegian startups have the highest probability to go bankrupt.

Both Ohlson (1980) and Bernhardsen (2001) argued that firm size was an important contributor to the probability of bankruptcy, and was included in Ohlson's (1980) recognized model that produced the O-score. Frank and Goyal (2009) emphasized how firm size influenced the capital structure, and presented firm size as a fundamental control variable. Ohlson (1980), Frank and Goyal (2009), and Bernhardsen (2001) used the natural logarithm of assets to determine

[10] The Pecking Order Theory concerns the capital structure within the organization, and was developed and introduced by Myers and Majluf (1984). The theory emphasizes how organizations prioritise sources of finance based on the law of least resistance. Internal financing is preferred over external when it is accessible, and within the latter are debt favoured over share capital. In addition, adverse selection (if it is in place) was enlarged due to tangibility, which resulted in a higher amount of debt.

the firm size, where both Bernhardsen (2001) and Ohlson (1980) also included other additional factors. However, both Statistics Norway (2019) and Skatteetaten (2020) used the number of employees to measure firm size.[11] The approach with the natural logarithm of assets suited the research purpose better since book-based values are analyzed. Also, Cassar (2004) found startup size and proportion of debt to be strongly correlated. Therefore, the firm size was measured through the natural logarithm of assets, *SIZE,* for observation *i* at time *t*.

As stated in the literature review, Lensberg, Eilifsen, and McKee (2006) and Altman, Fargher, & Kalotay (2011) explained how ratios that reflected financial distress could have been beneficial to include in bankruptcy circumstances. This point has been taken into consideration, and created a dummy, *financialdistress*, that indicated whether the startup found themselves in financial distress for observation *i* at time *t*. Whether the startups found itself in financial distress was measured through fulfillment of at least one of three indicators: (i) negative net income, (ii) negative working capital, or (iii) negative retained earnings.

Frank and Goyal (2009) acknowledged how growth would display the influence on leverage, financial distress, and free cash flow. Tradeoff theory noted how growth decreased the amount of leverage.[12] Nordal and Næs (2010, p.1) found that organizations with high expected future growth had a higher risk of bankruptcy. In addition, smaller companies had higher expected future growth rates compared to other organizations. Therefore, Nordal and Næs (2010, p.1) proposed a potential tradeoff between the risk of bankruptcy and high growth. As a result, growth was incorporated as a control variable, which was also in accordance with Frank and Goyal (2009) and Garcia de Olalla Lopez (2014).

[11] Statistics Norway's statistics display to which extent newly established organizations survive and grow, where companies over the age of five are removed from the study. Their first publication on this issue was in December 2004. In addition, Statistics Norway group organizations after industry, organizational structure, county, municipality, and size based on number of employees.

[12] The tradeoff theory of capital structure concerns the tradeoff between the amount of debt and equity to finance operations through considerations of benefits and costs. Kraus and Litzenberger (1973) introduced the theory with the consideration of debt benefits like tax savings and disadvantages like costs of financial distress (for instance bankruptcy). The main takeaway from this theory is the ability to demonstrate how organizations finance themselves with both debt and equity.

Growth was determined as the change in the natural logarithm of the total assets, *GROWTH,* for observation *i* at time *t*.

Garcia de Olalla Lopez (2014) argued for a control variable that reflected *risk*, since riskier organizations perceive debt as less attractive. The bankruptcy risk was influenced by whether the organization would meet their financial obligations. Therefore, more debt could enlarge the already risky business. Tradeoff theory implicated that higher risk, in general, and lower leverage are connected. Consequently, the risk was measured through the standard deviation of growth in sales, *RISK,* for observation *i* at time *t*. The standard deviation is often used by investors to measure risk, where a higher standard deviation would indicate more volatility and risk.

Furthermore, Garcia de Olalla Lopez (2014) pointed out how industry effects could influence the capital structure. Lemmon and Zender (2010) remarked several influences the economic environment for the organization had on the capital structure. For instance, Lemmon and Zender (2010) explained how debt could be preferred over equity. The capital structure is central for bankruptcy studies since the combination of equity and debt would influence the insolvency risk. Tradeoff theory found a negative correlation between leverage and growth. However, pecking order theory emphasized no apparent connection between leverage and industry categories. Frank and Goyal (2009) argued that industry factors gave no unique explanation. Therefore, the industry effects for which industry that went bankrupt the most was measured through an industry dummy, *industry,* for observation *i* at time *t*.

Lastly, 17 different financial ratios that Bellovary, Giacomino, and Akers (2007) found to be some of the most used ratios for bankruptcy examinations were included in this thesis. See appendix 2 for the 17 chosen financial ratios for observation *i* at time *t*. Financial ratios were one common approach to measure financial performance, which made it applicable for startups and the best possible way to answer the research question. These ratios reflected the four ratio categories practiced by Mayo and Rosenbloom (1975); (i) liquidity, (ii) activity/efficiency, (iii) profitability, and (iv) solvency. With the use of this measure of financial performance, the potential explanatory factor can be categorized and assessed on both a general and detailed level. Out of the 17 financial ratios, return on assets (ROA) and return on equity (ROE) were chosen to be the control variables that reflected profitability, in consideration of Rajan and Zingales (1995) and Frank and Goyal (2009) arguments.

Frank and Goyal (2009) argued for and included *tax considerations* in their paper. DeAngelo and Masulis (1980) demonstrated how the tax advantages of debt financing could be substituted with non-debt tax shields, which were negatively connected to leverage. However, in 2006 there was a Norwegian tax reform which influenced the taxation of dividends.[13] Therefore, for instance, entrepreneurs could reclassify their salaries onto dividends to escape taxation. Alstadsæter and Fjærli (2009) found how the Norwegian tax reform had influenced the leverage ratios, which increased until 2005 and subsequently decreased after the reform. In Frank and Goyal's (2009) study the tax effects showed the weakest performance in regards to influence on the capital structure. These findings concurred with Graham's (2000, 2003) results. As earlier mentioned, the capital structure was relevant for bankruptcy incidents since it influenced the combination of debt and equity. Since startups in a few instances paid out dividends and were unlikely to have tax effects, a variable that reflected tax considerations was not considered.

Descriptive Statistics

Table 1 presents the descriptive statistics of the central variables, on both non-bankrupt and bankrupt startups. Appendix 1 summarizes the characteristics of the explanatory and control variables. As illustrated in Table 1, Panel 1, the total observation of all startups aggregates to 537,590 in the period 2000-2017. From the entire observations, 3,900 formed the bankrupt startups and 533,690 the non-bankrupt startups. The dependent variable *bankrupt2* provided a larger mean than the median for the total amount of observations.

[13]Garcia de Olalla Lopez (2014) pointed out that before this reform tax exemptions were made in regards to dividend payment by private organizations.

The current ratio, *CUR*, was near twice the size for non-bankrupt startups (panel 3) compared to the bankrupt (panel 2). The non-bankrupt startups had a current ratio of 2,18 percent, which satisfied the generally known benchmark of 1,5-3 percent. For the bankrupt startups, however, the current ratio displayed 1,39 percent which was somewhat lesser than the benchmark. Therefore, this aspect indicated how bankrupt startups in the short-term would struggle to demonstrate financial strength.

Also, both bankrupt and non-bankrupt startups generated a negative return on assets (*ROA*). A negative ROA signified how startups, in general, struggled to utilize their assets. Therefore, it was interesting to note how both bankrupt and non-bankrupt startups generated a return on equity (*ROE*) way above the benchmark of 15-20 percent. Bankrupt startups held an ROE of 53 percent, whilst non-bankrupt produced 48 percent. Hence, the startups efficiently handled their investors' funds. However, it is essential to note that a high ROE could further be a risk indicator due to a small amount of equity compared to net income.

Table 2 displayed the Pearson correlation coefficient amongst the various variables in the sample period 2000-2017.In order to remove possible outliers, several variables have been windzorized prior to construction of the various tables models. First, *ROE, ROA, QC, WCOTA, RETTA, TDTTA, CTTA, QATTA, OITTA, LTDTTA, TDTE, CTCL*, and *ETTD* have been winsorized at 1 og 99 percentiles. Thus, *CUR, CLTTA,* and *RISK* were only winsorized at 99 percentiles since there were no major abnormalities, and a value of 0 was not an outlier compared to the rest of the values. However, *RISK, CTCL, ETTD* and *QC* was winsorized again at the 95 percentile, whilst *TDTE* and *ROE* at 5 and 95 percentiles. These variables were windzorized again since the variables showed tendencies of potential abnormalities. How the coefficients remained within 1 and -1 was a result of the Cauchy–Schwarz inequality. The main takeaway from the correlation matrix was how the coefficients, in general, were somewhat low.

Methodology

Selection of Variables

Table 1 presented the descriptive statistics with the different influences the observations had on bankruptcy. The number of bankrupt startups was modest compared to the non-bankrupt startups in the same dataset. Therefore, it was not given which of the variables that had the best explanatory power on bankrupt startups. Along with the mentioned arguments in the Data section, a logit model was estimated to best possible explain bankruptcy. Frank and Goyal's (2009) approach on how to narrow down variables in accordance with BIC was used as guidance, where necessary adjustments were made to fit the logistic regression model for bankruptcy.[14] The proposed binary logit model took the value 1 in the year of bankruptcy, and 0 if bankruptcy did not occur and for the bankrupt startups up until the year of bankruptcy. When all variables were included, the binary logistic regression model was the following[15]:

$$\begin{aligned} log\,(p^i/(1-p^i)) = {} & \beta_0 + \beta_1\, i.AGE_t^{\,i} + \beta_2\, SIZE_t^{\,i} + \beta_3\, GROWTH_t^{\,i} + \beta_4\, RISK_t^{\,i} \\ & + \beta_5\, ITTA_t^{\,i} + \beta_6\, financialdistress_t^{\,i} + \beta_7\, FEMALECEO_t^{\,i} + \beta_8\, CEOA_t^{\,i} \\ & + \beta_9\, ROE_t^{\,i} + \beta_{10}\, ROA_t^{\,i} + \beta_{11}\, CUR_t^{\,i} + \beta_{12}\, QC_t^{\,i} + \beta_{13}\, WCOTA_t^{\,i} + \beta_{14}\, RETTA_t^{\,i} \\ & + \beta_{15}\, TDTTA_t^{\,i} + \beta_{16}\, CATTA_t^{\,i} + \beta_{17}\, CTTA_t^{\,i} + \beta_{18}\, CLTTA_t^{\,i} + \beta_{19}\, QATTA_t^{\,i} \\ & + \beta_{20}\, OITTA_t^{\,i} + \beta_{21}\, LTDTTA_t^{\,i} + \beta_{22}\, TDTE_t^{\,i} + \beta_{23}\, CTCL_t^{\,i} + \beta_{24}\, ETTD_t^{\,i} + \epsilon_t \end{aligned} \tag{1}$$

Necessary actions were applied to reduce the number of inessential variables. Hastie, Tibshirani, and Friedman (2008) recognized several actions that could be done. The most generally known model selection criteria were the Bayesian information criterion (BIC) and the Akaike information criterion (AIC). The applicability of both AIC and BIC were tested for this thesis. The AIC criteria

[14] Frank and Goyal's (2009) article on capital structure decisions examined which factors were of importance when to explain market leverage in publicly traded American firms. The authors apply a linear regression model in their article.

[15] Where *i* reflect company *i,* and *t* reflect company *i* at time *t.*

for the logistic regression model included the binomial log-likelihood:

$$AIC = -\frac{2}{N} * loglik + 2 * \frac{d}{N} \tag{2}$$

Where d reflected the number of explanatory factors (variables), N considered the number of observations, k reflected number of parameters within the model, and *loglik* signified the maximized log-likelihood.

$$BIC = -2 * loglik + log\ (N)\ * k \tag{3}$$

The BIC was comparable with the AIC, where the number 2 was substituted with log(N). The BIC and AIC shared several benefits and contributed to the model selection. Hastie, Tibshirani, and Friedman (2008) emphasized how one method was not necessarily better than the other, which made the AIC and BIC proportionately equal. However, the BIC had empirically shown a tendency to penalize models that were complex and showed preference towards less complex models. As $N \to \infty$, the BIC had increased probability of selecting the correct as well as simpler model. In AIC's case, when $N \to \infty$ a more complex model was favoured.

For our model, the AIC and BIC both produced reasonable outcomes. However, since bankruptcy circumstances could be argued to be rather complex, the AIC was chosen to embrace the complexity and to narrow down the appropriate explanatory factors alongside significance levels. Besides, the AIC performed better than the BIC for our model. The logistic regression model with the lowest AIC was preferred since the AIC value should be as low as possible.

With a wide set of variables over a long period, the AIC produced no judgment alone on the initial logit model so it needed to be combined with significance. Accordingly, the variables were seen in light of their respective significance and the highest p-value was dismissed. For a logit model, the p-value was a suitable indicator for the assessment of significance for the different variables. The logistic regression model used in this thesis had a confidence interval at a 95 percent level. Therefore, if the p-value was 0,05 or lower, the variable would be acknowledged as significant. Subsequently, p-values greater than 0,05 were considered non-significant. Fisher's (1925) research was used as a basis for the 0,05 benchmark.

The non-significant variables were dropped from the binary logistic regression model so the AIC only considered the significant factors. However, significance alone was not sufficient to find the model with the lowest AIC. Therefore, the significant variables were then dropped after the lowest z-statistics to find the lowest AIC. The model with the lowest AIC reflected the variables with the best fit for the bankruptcy model. There was no distinction made between listed and non-listed since there were no bankrupt startups listed on Oslo Børs or Oslo Axess in this dataset.

The Robustness Test

After the previous steps were exercised, a robustness test was considered necessary. The robustness test consisted of several components: (i) significance test, (ii) significance test for the robust model clustered at industry level, (iii) robustness test of the significant variables clustered at industry level, and (iv) how the variables behaved for different kinds of startups under various circumstances.

First, the standard errors that have been estimated with the non-robust regression, were now estimated as a robust regression with robust standard errors. This step was taken to determine whether some variables gave a better AIC when the variables were robust, and to check if the variables were still significant. Also, these significant, robust variables were tested for their respective z-statistics to see which variables that had the optimal combination of significance and z-statistic.

Second, the standard errors were clustered at the industry level. Petersen (2009) and Cameron, Gelbach, and Miller's (2011) articles were applied to understand the effect of clustered standard errors, and how it could be relevant for the logistic regression model. The unbalanced panel data in this study were more numerous in one dimension (non-bankrupt startups), which made clustered standard errors highly relevant when the panel data were highly unbalanced. Correlations within clusters could miscalculate the standard errors of the regression coefficient estimates and the possibility of biased standard errors and parameter estimates for factors that could affect bankruptcy. Thus, it was important to adjust for clusters. For this thesis, industry clusters were adjusted for since startups in the different industries could have been quite similar or related to each other in their developing years. Since the panel data in this thesis was unbalanced, there was no necessity for double-clustering in the same manner as Frank and Goyal (2009).[16] Subsequently, the logistic regression model was recalculated in the same manner as the initial model but now with standard errors clustered at the industry level. Consequently, the new model would demonstrate potential robust factors.

Third, variables were tested to see if the recognized explanatory patterns applied to different kinds of startups. Lemmon and Zender (2010) remarked several influences the economic environment for the organization had on the capital structure. For instance, Lemmon and Zender (2010) explained how debt could be preferred over equity. Therefore, the startups have been, with a combination of aspects by Frank and Goyal (2009) and Garcia de Olalla Lopez (2014), divided after growth, size, and tangibility.[17] Since no bankrupt startups were listed on Oslo Børs/Axess, a separation between listed and non-listed was not performed.

Firms with strong growth were considered by Myers (1977) to hold more equity to refrain a potential difficulty with debt overhang. The relationship between debt problems and startup growth is often discussed, where, for instance, Cassar (2004) found startup size and proportion of debt to be strongly correlated. For tangibility, both Frank and Goyal (2009) and Rajan and Zingales (1995) remarked how debt ratios were positively influenced by a greater amount of

[16] Frank and Goyal (2009) double clustered, where the authors clustered at both year and firm level.
[17] Garcia de Olalla Lopez (2014) started with sorting organizations by listing status and size, before these categories were divided into growth, size, and tangibility. Frank and Goyal (2009) measured dividend- and non dividend-paying firms and market to book assets ratio instead of Garcia de Olalla Lopez' (2014) tangibility and growth.

tangible assets. The number of tangible assets was central for investors in case of potential bankruptcy, which according to Watson and Everett (1996), made tangibility a relevant measure. These arguments strengthened the importance of dividing by growth, size, and tangibility, on both a high and low level for the startups.

Similarly to Frank and Goyal (2009) the levels of high and low were seen in perspective with the 66th and 33rd percentile in annual cross-sections. Therefore, the startup was classed as high growth, if the change in the log of assets surpassed the 66th percentile. Respectively, a classification of a low growth startup followed for a change in the log of assets below the 33rd percentile. To correctly detect growth, the dataset was adjusted to start in 2001. A startup was considered of great size if the log of total assets exceeded the 66th percentile, and classified as small if the log of total assets were under the 33th percentile. Lastly, a startup was acknowledged with high tangibility if the ratio of tangible assets to total fixed assets surpassed the 66th percentile. Respectively, if the tangibility ratio was below the 33th percentile, then the startup was classified with low tangibility.

Behaviour of the Core Financial Explanatory Factors

Once the previous steps were accomplished, then the robust core factors for bankrupt startups would be identified. The AIC criterion functioned as a goodness of fit determinant itself, but to further validate the model, supplementary actions were considered. The central additional method here was a cutoff for the classification of the core model as well as the receiver operating characteristic (ROC) curve.[18] The ROC curve described how well a parameter could distinguish between two groups, which in our case were bankrupt and non-bankrupt startups. However, since both industry and taxation effects were disregarded in the logistic regression model, it could regardless be relevant to observe how the core factors

[18] "lsens" is the Stata code that was used to check where the lines (sensitivity and specificity) cross to estimate the classifications correctly, and how that would later result in a ROC curve. The cutoff in this thesis was approximately 0.0040885.

perform. Therefore, the robust core factors were observed for: (i) before and after the taxation reform in 2006, and (ii) which industry that influenced bankruptcy the most.

After, the proposed logit model (1) with only the recognized robust core factors will be estimated to see how the factors behave over time. This thesis has until this point not considered any tax effects nor the tax reform from 2006. Alstadsæter and Fjærli (2009) observed the effect of the Norwegian tax reform in 2006 on organizations as having great influence on the taxation of dividends and a decrease in debt ratios. [19] Distinguishing between the periods before and after the taxation reform could allow for exploration of a potential impact on the important ratios and factors for startups, in addition to the debt ratios. However, some could argue how such tax effects could have been shown through a tax variable. But, in Frank and Goyal's (2009) study the tax effects showed the weakest performance in regards to influence on the capital structure. These findings concurred with Graham's (2000, 2003) results. Therefore, the robust logistic regression model was demonstrated for the period 2000-2005, 2006-2017, and the whole sample period.[20] As a starting point, every regression was calculated with the help of clustered standard errors at industry level and the corresponding sample of observations that were adopted in the variable selection process.

Then, the variables were examined in light of which industry that influenced bankruptcy the most. Since the logistic regression model had standard errors clustered at the industry level, an industry variable was not included in the model. Hence, when a variable was clustered at, while also included as an independent variable, then the variable would always be significant within the model since it allowed for intragroup correlations. In order to avoid this bias, the industry effects were exhibited through which industry had the most powerful

[19]Garcia de Olalla Lopez (2014) pointed out that before this reform tax exemptions were made in regards to dividend payment by private organizations. As a result, salaries were reclassified into dividends to escape taxation.

[20] The two most important changes with the taxation reform from 2006 is tax on dividends and changes in top tax, where each of these draws in opposite directions. However, since tax on dividends dominates, the total effect of taxation reform stimulates redistribution of capital (Lian, Nesbakken, & Thoresen, 2013).

influence on bankruptcy based on the robust core factors without clustered industries.

Results

In this part of the thesis, the main results from our logistic regression model will be presented. The structure follows the same as in the methodology: First, the main findings from the variable selection process for the bankrupt startups will be presented. After, a robustness test will be conducted on the various variables, and show how they perform. Lastly, the core logistic regression model for explaining bankrupt startups in the period 2000-2017 will be presented. If the potential explanatory factors are influenced by either the taxation reform in 2006 or industries will be shown through different tables.

Selection of Variables

The results from the selection process of the various variables were recorded in Table 3. To properly understand Table 3, the table needs to be read from the bottom and up. The variable at the bottom had the highest p-value when the logistic regression model contained all variables and reflected the starting point for studying this table. Accordingly, variables were removed per significance (starting at the bottom) until the marked line in the table. On a general note, the variables with a positive coefficient indicated how bankruptcy was more likely to occur, and the variables with negative coefficients indicated how bankruptcy was less likely to occur. Table 4 was structured in the same manner as Table 3 and considered the same variables but now with robust standard errors. Also, Table 4 would not function as a robustness test alone since Table 4 only indicates which of the variables that were both robust and significant. The main takeaway from Table 4 was which variables that were robust and significant, and applicable for further use in the logistic regression model.

For instance, Working Capital over Total Assets (*WCOTA)* had a p-value of 0.697 in Table 3. Column (5) reported the regression's McFadden pseudo R2, and column (6) reported the AIC for the same logistic regression. The p-value in column (4) was for the respective variable, in the same model as the reported values in column (5) and (6). Once *WCOTA* has been acknowledged as the factor with the highest p-value, then a logistic regression was run with *WCOTA* alone to detect the coefficient estimate in column (1), z-statistics in column (2), as well as the own R2 in column (3). After *WCOTA* has been examined, the regression was rerun without *WCOTA* and the same process was repeated. This process was repeated until there was a significant model present. Then, in the same manner as with the p-values but now with z-statistics, variables were disregarded until there was only one variable remaining as displayed in Table 5.

The line in Table 3 signified the separation between the non-significant and significant factors. There were several more significant variables than non-significant, which still gave several possible core factors for explaining bankruptcy in Norwegian startups. In addition, the significant financial ratios were nearly equally distributed among the ratio categories, which could signify that profitability, solvency, activity, and liquidity had an equal influence on the occurrence of bankruptcy. However, both significant profitability and activity ratios had negative coefficients. Therefore, the ratios within these categories would reflect how bankruptcy was less likely to occur. Hence, significant solvency and liquidity ratios, due to positive coefficients, displayed how bankruptcy was more likely to occur.

As Frank and Goyal (2009) pointed out, the firm size was a variable that reflected a marked-based definition of leverage. As a result, since this thesis used a book-based definition of leverage, the result for *SIZE* as a non-significant variable was as expected. In addition, the *AGE* variables came across as some of the most significant variables, which highlighted the importance of incorporating *AGE*. The *AGE* variable reflected the operating year for the startup. Moreover, since *2.AGE, 4.AGE* and *5.AGE* were significant at a 99 percent confidence interval, it highlighted the relevance of including accounting information for all relevant years since AGE influenced bankruptcy between the operating years of three to six.

The Robustness Test

Additional results from the robustness test, as explained in the methodology, was reported in Table 4 and Table 5 for the regression with clustered standard errors and Table 6 for the behaviour under different circumstances. Table 4 was similar to Table 3, but the main difference here was how the initial logistic regression model was clustered for industries. Therefore, Table 4 can be read and interpreted in the same manner as Table 3. Hence, the least significant variables were located at the bottom, and all the variables above the marked line indicated the significant factors.

Further investigation of the best AIC model was performed in Table 5, so the variables with the lowest z-statistics were removed until only one variable was left. This step was done to test whether there were any better underlying AIC and check the robustness of the different variables. Current Liabilities to Total Assets (*CLTTA*) proved to be the variable that had the best z-statistic while also significant. However, *CLTTA* did not have the most adequate AIC. The logistic regression with all the significant, robust variables showed to be the model with the best AIC when standard errors were clustered on industries. Thus, all variables over the marked line in Table 4 will be applied further to recognize the optimal logistic regression model.

Table 5 presented the results from the robustness test of the significant, robust variables. From the 38 initial variables, 17 variables constituted the robust, significant ones. Almost all *i.AGE* were considered as the most robust and significant variables out of the total 17 variables, except *0.AGE*, *1.AGE* and *6.AGE*. *0.AGE*, *1.AGE* were omitted since the variables were empty, and *6.AGE* was removed due to collinearity. The *AGE* variable reflected the operating year for the startup. Several *i.AGE* variables would indicate that *i.AGE* was with more than 95 percent confidence a reliable variable within this study. Also, the coefficient variable estimates were both negative and positive which indicated how the different operating years would have varied effects on the bankruptcy occurrence. Since *2.AGE* and *3.AGE* were some of the most significant variables with a positive coefficient estimate in Table 5, it indicated that startups with operating year two and three were more likely to go bankrupt.

The detected significant, robust factors were almost the same as the significant, non-robust variables, except from one, Total Debt to Total Assets (*TDTTA*). *TDTTA* came as an additional robust variable after the robustness test was done, and measured how much of the assets that consisted of debt. The robustness test allowed for correlation among organizations within the same industry. Therefore, *TDTTA* could occur as a significant, robust variable, and not as a non-robust variable. Overall, the result from the implementation of robust actions for the logistic regression model were 17 variables that qualified as potentially robust, core factors for explaining bankruptcy in Norwegian startups.

In order to acknowledge which of the 17 variables that were the actual core factors for explaining bankruptcy, the AIC was central. Several possible combinations of the significant variables were tested for detecting the best AIC, which resulted in one conclusive outcome. The outcome with the best AIC was with all the 17 significant variables, which was acknowledged in Table 4 and Table 5. The reason for why the AIC acknowledged 17 variables, and not fewer, concerned how AIC favors complexity. Also, this aspect could be interpreted as how bankruptcy was complex and consisted of several different components.

After the robust core factors were detected, all variables were tested in regards to other robustness measures. To check for overall robustness, no time consideration was made, so the dependent variable *bankrupt* was applied. In accordance with Frank and Goyal (2009) and Garcia de Olalla Lopez (2014), the startups were categorized into the following categories: tangibility, size, and growth. The results are presented in Table 6. The selection process was redone for annual cross-sections. The core variables that passed the robustness test were signalized through a mark of the variable in bold. The main takeaway from the robustness test was how the core variables appeared more frequently in different circumstances compared to the other variables. The exception was *SIZE* and

WCOTA that appeared quite often, with both negative and positive signs. In addition, the core variables appeared most of the time with the same sign as of the core model, which indicated that the core factors were, in fact, robust.

Since no bankrupt startups were listed on Oslo Børs or Oslo Axess, a robustness test was not conducted within this group. Therefore, no conclusion can be drawn in regards to whether listed and non-listed bankrupt startups had comparable performance under various levels of agency costs, financially constrained and unconstrained, diverse bankruptcy costs, as well as various informational asymmetries.

Behaviour of the Core Financial Explanatory Factors

Table 7 presented the core logistic regression model for explaining bankruptcy in Norwegian startups. Whether the model had a good fit for describing bankruptcy, was determined through the goodness of fit tests. The results from the goodness of fit tests are summarized in Table 8. The cutoff for the classification model and the respective results, displayed in Table 9, signified an overall rate of correct classification estimated to 67.47 percent, with 70.76 percent of the bankrupt startups correctly classified (sensitivity) and 67.46 percent of the non-bankrupt startups correctly classified (specificity).

Afterward, the ROC curve was reckoned where the curve can be seen in Figure 2. The area under the ROC curve was approximately 0.7490, which was an acceptable outcome. Since the ROC curve had a higher line than 45 degrees, it had a more favorable power than a line of less than 45 degrees. Thus, the flip of a coin would be equal to a line of 45 degrees. The best possible ROC curve would have had an angle that was 90 degrees, which would have indicated neither no false negatives or positives. Hence, the goodness of fit examination confirmed the sufficient power the model had for explaining bankruptcy, which acknowledged the model and allowed for further use of the robust, core factors. Nevertheless, it is necessary to highlight how no statistical model is 100 percent accurate since factors, from both inside and outside the logistic regression, could affect the accuracy.

The effects of the tax reform in 2006 are reported in Table 10 and Table 11. On a general note, there were minor, marginal changes in almost all robust, core variables with clustered standard errors. Thus, the taxation reform in 2006 had barely any effect for bankruptcy in Norwegian startups. These minor effects were as expected since startups seldom pay dividends, and the taxation reform mainly concerned taxation of dividends. However, there could be arguments for entrepreneurs that could have reclassified salaries into dividends to avoid tax. These findings did not support such hypotheses since there were minor changes in the coefficients for the different core, robust variables. Also, these findings corresponded with Frank and Goyal (2009), Graham (2000), and Graham's (2003) results on how tax effects had a minor explanatory impact on capital structure. Therefore, the taxation results could also be interpreted as a minimal effect on the capital structure for bankruptcy in Norwegian startups.

Which industry that influenced bankruptcy the most are reported in Table 12. Industry 5, 6, 8, and 9 were the industries that had the most considerable influence on bankruptcy. These industries reflected (i) water supply; sewerage, waste management, and remediation activities, (ii) construction, (iii) transportation and storage, and (iv) accommodation and food service activities. One thing these industries had in common was the number of tangible assets. Tangible assets often bind capital and experience difficulties to create profit. Also, these assets could be of high value that makes them expensive to buy, which results in a need for available financing that could lead to more debt. It is interesting to observe how industry 13, which concerns professional, scientific, and technical activities, had a somewhat average effect on bankruptcy. This industry is often given great space in the media and attention in general. In contrast, industry 13 usually holds more intangible assets than industry 5, 6, 8, and 9.

The final core model, as earlier mentioned, consisted of seventeen robust factors. In order to narrow down the seventeen robust, core factors, even more, a look at the research question was made. The research question concerned the financial explanatory factors of bankruptcy in Norwegian startups, which would imply that factors that were not acknowledged as a recorded number in the financial statements could be deliberately disregarded. Therefore, the variables *AGE*, *FEMALECEO*, and *CEOA* were not considered as financial factors. Hence, eleven variables were the actual financial explanatory factors for bankruptcy in Norwegian startups. These eleven variables concerned all of the four ratio categories, but the solvency category was most numerous.

However, further considerations could be made to correctly answer the research question based on the remaining coefficients. The negative coefficients reflected how bankruptcy was less likely to occur for every increase of unit of the relevant variable. Therefore, *ITTA*, *RETTA*, *TDTTA*, *CTTA*, *TDTE*, and *CTCL* were purposely ignored due to negative coefficients. Subsequently, the following five factors had a positive coefficient: *RISK, financialdistress, CLTTA, QATTA,* and *ETTD*. Out of these variables, *RISK,* and *financialdistress* were control variables, while *CLTTA, QATTA,* and *ETTD* were financial explanatory factors. For those three financial explanatory factors, a one unit increase in one of those variables, the log odds of going bankrupt would have increased by respectively 0.2343, 0.4727, and 0.1079 holding all other variables constant. Respectively, for a one unit increase in one of those variables, the odds of going bankrupt would have increased by a factor of respectively $e^{0.2342575} = 1.264$, $e^{0.4726748} = 1.604$, and $e^{0.1079357} = 1.114$, holding all other variables constant. *CLTTA* and *ETTD* were ratios that reflected solvency, while *QATTA* showed liquidity. Therefore, in general, one could say that failed startups struggled to meet their financial obligations, took on too much debt, and struggled to transform assets to cash quickly.

The results that concern the explanatory factors validated how bankrupt startups overall had worse financial performance than the non-bankrupt startups. Both liquidity and solvency ratios concern the financial pulse of the organization, which showed to be the most central ratios within this study. Therefore, the results indicated that bankrupt startups struggled with both short-term and long-term financial obligations. The low amount of liquid assets for startups were acknowledged by the results in *QATTA*. However, both the current and the quick ratio were not considered as main explanatory factors for bankruptcy. These ratios indicated that the organization was able to pay their liabilities and generated cash for the short-term, even though the startups did not have a solid amount of liquid assets. With this in mind, the interesting aspect was when these arguments are seen in relevance with the *financialdistress* variable. Since *financialdistress* had a positive coefficient estimate, it gave an increased probability of bankruptcy. Since the startups were influenced by financial distress, it indicated that the startups either (i) had negative net income, (ii) negative working capital, or (ii) negative retained earnings. Since *WCOTA* and *OITTA* were both non-significant, there can be said with greater confidence that negative retained earnings is the most central underlying determinant of financial distress. Thus, startups did not satisfactory retain earnings from net income to save for shareholder's equity.

Implications, Limitations, and Future Research

Practical and Theoretical Implications

Firstly, the results from the ratio analysis recognized how there were less liquid assets, and problems with both short and long-term financial obligations. Since the solvency ratios were the most dominant explanatory factors, it indicated that Norwegian startups had a negative net worth and a non-manageable debt level.
Since there were also less liquid assets within the startups, one important issue is the amount of untapped cash within the organization. Untapped cash inside the company compared to alternative funds from banks, venture capitalists, or angel investors is to a greater extent inexpensive. Thus, when the cash is released, opportunities for investment purposes in future growth opens up or down payment of debt.

The findings in this thesis could be used to better understand the warning signals for bankruptcy in startups, as well as raised awareness of not only the intrapersonal aspects associated with startups. Therefore, venture capitalists, angel investors, and startup accelerator programs could apply this thesis' findings when they evaluate startups for investment purposes. It is natural to assume that they already have financial indicators that they lean on, but these findings could contribute to even more indicators. In addition, entrepreneurs could use the findings to enhance the startups' financial performance. The bankrupt startups struggled to meet their financial obligations and took on too much debt. Nevertheless, most importantly, these findings could perhaps contribute to a greater amount of startups that could cross the chasm.

Nonetheless, one could generally have questioned the knowledge and insight the different entrepreneurs have on the various financial levels that they should aspire to reach. Awareness of benchmark and industry specifics requires a comprehensive understanding of the financial statement and industry, which is often achieved over time and through experience. Bruce (2008) remarked on how financial ratios are beneficial as the ratios could contribute to evaluating the efficiency and effectiveness of the organization.

The authorities could also find these findings useful, both for investment purposes and increased awareness. Since startups contribute to the Norwegian economic environment, it would be natural for the government to watch over and look for potential improvements in regards to, for instance, legislation. The Australian government has created an app where it is possible for small business owners to fill in their own financial information and then compare the organization's performance against the industry norm (Australian Government, 2019). This allows for small business owners, as well as startups, to properly understand where improvement could be done. The data that creates the comparison foundation in the app is based on official reported numbers by companies, but the numbers have been anonymised by the Australian government (Australian Government, 2019). The approach by the Australian government on how to increase awareness and knowledge through the use of an easily accessible tool as an app, is something the Norwegian authorities could get inspiration from.

Limitations and Future Research

The range of limitations on this thesis has been minimized as much as possible, but however some remains. As reflected throughout this thesis, research on startups has previously mainly been on intrapersonal aspects, and rarely on exclusively financial reasons. Therefore, this thesis has been leaning on bankruptcy and capital structure research for public and listed organizations and acknowledged indicators that have not previously been tested on startups. As a result, some financial aspects that concerned startups could have been excluded. Interaction effects have not been considered, nor dynamic effects or firm fixed effects.[21] Firm fixed effects are statistically important, but were not important for this thesis' research purpose.

Future research on startups in Norway could be to examine whether the geographical location has an important role in non-bankrupt startups. Startup accelerator programs are mostly positioned in Oslo. Therefore, the effect of geographical location, whether the startup is located in Kirkenes or Oslo, could be interesting to investigate. For instance, Innovation Norway has several offices spread across both Norway and other countries.[22] One could interpret such presence as an initiative to be present wherever the entrepreneur and startup are placed.

Another possibility would be to test the recognized bankruptcy prediction models, and how great the models predict bankruptcy for startups. For instance, the applicability of both Ohlson's (1980) O-score and Altman's (1968) Z-score could be tested. The results from the test could be compared to the explanatory power the bankruptcy models have on public and listed companies. If the bankruptcy prediction models show great relevance in predicting bankruptcy one

[21] For the interested reader, research connected to the dynamic effects could be found in for instance Leary and Roberts (2005) and Lemmon, Roberts, and Zender (2008).

[22] Innovation Norway is one of the most influential mechanisms to facilitate growth and innovation for Norwegian companies and industries with help from the Norwegian Government. Their daily operations consider project financing and increased knowledge among small and medium-sized companies with growth ambitions. Further, they offer financing, advisory services, knowledge, network, and profiling. The main ambition for Innovation Norway is to contribute to creating a better Norwegian business environment.

to two years ahead of time, then it could be relevant for both investors and startup accelerator programs to use such models.

Conclusion

This thesis has examined Norwegian startups within the time period 2000-2017 in order to detect potential financial explanatory factors for bankruptcy in Norwegian startups. 38 variables were introduced as possible explanatory variables based on usefulness in previous research on both capital structure and bankruptcy. The financial explanatory factors were examined with the help of a binary logistic regression model, that included several financial aspects of the organization.

From these 38 variables, three variables provided the central financial explanatory factors for bankruptcy in Norwegian startups: Equity to Total Debt (*ETTD*), Quick Assets to Total Assets (*QATTA*), and Current Liabilities to Total Assets (*CLTTA*). Therefore, in general, one could say that since the solvency ratios were the most dominant explanatory factors, which indicate how Norwegian startups have a negative net worth and a non-manageable debt level. Since Norwegian startups hold less liquid assets, one important issue is the amount of untapped cash within the organization. Untapped cash inside the company is to a greater extent inexpensive compared to other funds. Thus, when the cash is released, opportunities for investment purposes in future growth opens up or potential down payment of debt.

The industries that experienced bankruptcy the most were (i) water supply; sewerage, waste management, and remediation activities, (ii) construction, (iii) transportation and storage, and (iv) accommodation and food service activities. One thing all these four industries had collectively, was that their inventory had more tangible than intangible assets. Therefore, the assets hold more capital and could be more difficult to quickly transform assets into cash.

As the recognized statistician Box (1979) pointed out “all models are wrong, but some are useful.” Therefore, we hope that our identified financial explanatory factors will be of use in the startup field, as well as potentially spark further research. Several variables have similarities that support how underlying incremental variations are central. Hopefully, these findings could contribute to a larger amount of startups that cross the chasm.

Reference List

Adkins, L. C., Hill, R. C. (2011). *Using Stata For Principles of Econometrics, fourth edition*. New York: Wiley.

Alstadsæter, A. & Fjærli, E. (2009). Neutral Taxation of Shareholder Income? Corporate Responses to an Announced Dividend Tax. *International Tax and Public Finance*, 16 (4), 571-604. Doi: 10.1007/s10797-009-9107-2

Altman, E. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, 23(4), 589-609. Doi: 10.2307/2978933

Altman, E., Fargher, N., & Kalotay, E. (2011). A Simple Empirical Model of Equity-Implied Probabilities of Default. *The Journal of Fixed Income*, 20(3), 71-85.

Altman, E., Iwanicz-Drozsowska, M., Laitinen, E., & Suvas, A. (2016). Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model. *Journal of International Financial Management and Accounting*, 28(2), 131-171. Doi: 10.1111/jifm.12053

Australian Government. (2019). Small business benchmarks. Retrieved from https://www.ato.gov.au/Business/Small-business-benchmarks/

Bammens, Y. P. M., & Collewaert, V. (2014). Trust Between Entrepreneurs and Angel Investors: Exploring Positive and Negative Implications for Venture Performance Assessments. *Journal of Management*, 40(7), 1980-2008. Doi: 10.1177/0149206312463937

Beaver, W. (1966). Financial Ratios As Predictors of Failure. *Journal of Accounting Research*, 4, 71-111. Doi: 10.2307/2490171

Bellovary, J., Giacomino, D., & Akers, M. (2007). A Review of Bankruptcy Prediction Studies: 1930 to Present. *Journal of Financial Education*, 33(1),1-42.

Bernhardsen, E. & Larsen, K. (2007). Modelling Credit Risk in the Enterprise Sector - Further Development of the SEBRA model. *Norges Bank Economic Bulletin*, 78(3), 102-108.

Bernhardsen, E. (2001). *A Model of Bankruptcy Prediction* (Master's thesis). University of Oslo, Oslo.

Berzins, J., & Bøhren, Ø. (2009). Unoterte Aksjeselskaper Er Viktige, Uutforskede og Spesielle. *Praktisk Økonomi & Finans*, 25(2), 65-76.

Berzins, J., Bøhren, Ø. & Stacescu, B. (2012). Stockholder Conflicts and Dividend Payout. CCGR Working Paper, 5, 1-45.

Box, G. E. P. (1979). Robustness in the Strategy of Scientific Model Building. In Launer, R., & Wilderson, G. (Red.), *Robustness in Statistics* (p. 201-236). New York: Academic Press.

Bruce, E. (2008). Examining the Numbers. *Institute of Internal Auditors*, 65(2), 45-49.

Brüderl, J., Preisendörfer, P., & Ziegler, R. (1992). Survival Chances of Newly Founded Business Organization. *American Sociological Review*, 57(2), 227-242. Doi: 10.2307/2096207

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust Inference With Multiway Clustering. *Journal of Business & Economic Statistics*, 29 (2), 238-249. Doi: 10.1198/jbes.2010.07136

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In Search of Distress Risk. *The Journal of Finance*, 63(6), 2899-2939.

Cantamessa, M., Gatteschi, V., Perboli, G., & Rosano, M. (2018). Startups' Roads to Failure. *Sustainability*, 10(7), 1-19. Doi: 10.3390/su10072346

Cassar, G. (2004). The Financing of Business Start-Ups. *Journal of Business Venturing*, 19(2), 261-283. Doi: 10.1016/S0883-9026(03)00029-6

Cochran, A. (1981). Small Business Mortality Rates: A Review of the Literature. *Journal of Small Business Management*, 19(4), 50-59.

Collins, R., & Green, R. (1982). Statistical Methods for Bankruptcy Forecasting. *Journal of Economics and Business*, 34(4), 349-354. Doi: 10.1016/0148-6195(82)90040-6

Cressy, R. (1996). Are Business Startups Debt-Rationed? *The Economic Journal*, 106(438), 1253-1270. Doi: 10.2307/2235519

Dakovic, R., Czado, C., & Berg, D. (2007). Bankruptcy Prediction in Norway: A Comparison Study. *Applied Economics Letters*, 17(17), 1739-1746. Doi: 10.1080/13504850903299594

DeAngelo, H. & R. Masulis. (1980). Optimal Capital Structure under Corporate and Personal Taxation. *Journal of Financial Economics*, 8(1), 3-29. Doi: 10.1016/0304-405X(80)90019-7.

Demartini, P. (2018). Innovative Female-Led Startups. Do Women in Business Underperform? *Administrative Sciences*, 8(4), 70. Doi: 10.3390/admsci8040070

DNB. (2020, February 26th). Hvordan Lykkes Med Investeringer i Startups? [Podcast]. Retrieved from https://podcasts.apple.com/no/podcast/hvordan-lykkes-med-investeringer-i-startups/id995845886?i=1000466728068

Drover, W., Busenitz, L., Matusik, S., Townsend, D., Anglin, A., & Dushnitsky, G. (2017). A Review and Road Map of Entrepreneurial Equity Financing Research: Venture Capital, Corporate Venture Capital, Angel Investment, Crowdfunding, and Accelerators. *Journal of Management*, 43 (6), 1820-1853. Doi: 10.1177/0149206317690584

Eklund, T., Larsen, K., & Bernhardsen, E. (2001). Model for Analysing Credit Risk in the Enterprise Sector. *Norges Bank Economic Bulletin*, 72(3), 99-106.

European Commission. (2015). User guide to the SME Definition. Retrieved from https://ec.europa.eu/regional_policy/sources/conferences/state-aid/sme/smedefinitionguide_en.pdf

Fisher, R. A. (1925). Statistical Methods for Research Workers (11th ed.). Edinburgh: Oliver and Boyd.

Frank, M. Z., & Goyal, V. K. (2009) Capital Structure Decisions: Which Factors are Reliably Important? *Financial Management*, 38(1), 1-37. Doi: 10.2139/ssrn.567650

Fredland, E. & Morris, C. (1976). A Cross Section Analysis of Small Business Failure. *American Journal of Small Business*, 1(1), 7-18.

Garcia de Olalla Lopez, I. (2014). Essays in Corporate Finance (11). Oslo: BI Norwegian Business School.

Graham, J. R. (2000). How Big Are the Tax Benefits of Debt? *The Journal of Finance*, 55 (5), 1901-1941. Doi: 10.1111/0022-1082.00277

Graham, J. R. (2003). Taxes and Corporate Finance: A Review. *Review of Financial Studies*, 16 (4), 1075-1129. Doi: 10.1093/rfs/hhg033

Harris, C., & Jenkins, M. (2006). Gender differences in risk assessment: Why do women take fewer risks than men? *Judgment and Decision Making,* 1(1), 48–63.

Hastie, T., Tibshirani, R., and Friedman, J. (2008). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (2nd ed.). Stanford: Springer.

He, X., Inman, J., and Mittal, V. (2008). Gender jeopardy in financial risk taking. *Journal of Marketing Research,* 45(4), 414–424.

Jackendoff, N. (1962). *A Study of Published Industry Financial and Operating Ratios*. Philadelphia: Bureau of Economic and Business Research.

Jones, S., & Hensher, D. A. (2004). Predicting Firm Financial Distress: A Mixed Logit Model. *The Accounting Review*, 79(4), 1011-1038.

Karels, G. and A. Prakash. (1987). Multivariate normality and forecasting of business bankruptcy. *Journal of Business Finance & Accounting*, 14(4), 573-593.

Kensinger, J. (2010). *Research in Finance* (v. 26.). Bingley: Emerald Publishing Limited.

Konkursrådet. (2011). Country report - the Norwegian bankruptcy system. Retrieved from http://www.konkursradet.no/country-report-thenorwegian-bankruptcy-system.5305225-300329.html

Kraus, A. & Litzenberger, R. H. (1973). A State-Preference Model of Optimal Financial Leverage. *Journal of Finance*, 28 (4), 911–922. Doi:10.1111/j.1540-6261.1973.tb01415.x

Laitinen, E. & Laitinen, T. (2000). Bankruptcy prediction: Application of the Taylor's expansion in logistic regression. *International Review of Financial Analysis*, 9 (4), 327-349. Doi: 10.1016/S1057-5219(00)00039-9

Leary, M. T., & Roberts, M. R. (2005). Do Firms Rebalance Their Capital Structures? *Journal of Finance*, 60(6), 2575-2619.

Lemmon, M. L., Robers, M. R., & Zender, J. F. (2008) Back to the Beginning: Persistence and the Cross-Section of Corporate Capital Structure. *Journal of Finance*, 63(4), 1575-1608.

Lemmon, M. L., & Zender, J. F. (2010). Debt Capacity and Tests of Capital Structure Theories. *The Journal of Financial and Quantitative Analysis*, 45 (5), 1161-1187. Doi: 10.1017/S0022109010000499

Lensberg, T., Eilifsen, A., & McKee, T. (2006). Bankruptcy Theory Development and Classification Via Genetic Programming. *European Journal of Operational Research*, 169(2), 677-697. Doi: 10.1016/j.ejor.2004.06.013

Li, H., Lee, Y., Zhou, Y., & Sun, J. (2011). The Random Subspace Binary Logit (RSBL) Model for Bankruptcy Prediction. *Knowledge-Based Systems*, 24(8), 1380-1388.

Lian, B., Nesbakken, R., & Thoresen, T. O. (2013). Skattesystemets omfordelende effekt 2005-2013 (SSB rapport 29/2013). Retrieved from https://www.ssb.no/offentlig-sektor/artikler-og-publikasjoner/_attachment/125600?_ts=13f7b1d5ba8

Lukason, O. & Camacho-Miñano, M. (2019). Bankruptcy Risk, Its Financial Determinants and Reporting Delays: Do Managers Have Anything to Hide? *Risks*, 7(3), 1-15. doi: 10.3390/risks7030077

Mayo, H. & Rosenbloom, B. (1975). Ratio Analysis For The Small Businessman. *Journal of Small Business Management*,13 (1), 9-11.

Morris, R. (1997). *Early Warning Indicators of Corporate Failure: A Critical Review of Previous Research and Further Empirical Evidence* (1st Edition). Aldershot, Hants, England: Avebury.

Myers, S. C. (1977). Determinants of Corporate Borrowing. *Journal of Financial Economics*, 5 (2), 147-175. Doi: 10.1016/0304-405X(77)90015-0

Myers, S. C. & Majluf, N. S. (1984). Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have. *Journal of Financial Economics*, 13 (2), 187–221. Doi:10.1016/0304-405X(84)90023-0

Nordal, K. B. & Næs, R. (2010). The Relationship between Bankruptcy Risk and Growth for Non-listed Firms. *Working Papers Norges Bank*, *2010* (31), 1-30.

Næringslivets Hovedorganisasjon. (2020). Fakta Om Små og Mellomstore Bedrifter (SMB). Retrieved from https://www.nho.no/tema/sma-og-mellomstore-bedrifter/artikler/sma-og-mellomstore-bedrifter-smb/

Ohlson, J. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, 18(1), 109-131. Doi: 10.2307/2490395

Petersen, M. (2009). Estimating Standard Errors in Finance Panel Data Sets. Review of Financial Studies, 22 (1), 435-480. Doi: 10.2139/ssrn.661481.

Pompe, P., & Bilderbeek, J. (2005). The Prediction of Bankruptcy of Small- and Medium-Sized Industrial Firms. *Journal of Business Venturing*, 20(6), 847-868. Doi: 10.1016/j.jbusvent.2004.07.003

Rajan, R. & L. Zingales. (1995). What Do We Know about Capital Structure: Some Evidence from International Data. *Journal of Finance*, 50 (5), 1421-1460. Doi: 10.1111/j.1540-6261.1995.tb05184.x

Ruback, R. (1984). Estimation of Implicit Bankruptcy Costs: Discussion. *The Journal of Finance*, 39 (3), 643-645. Doi: 10.2307/2327922

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research Methods for Business Students* (7th ed). Essex: Pearson Education Limited.

Skatteetaten. (2020). Inntektsfradrag ved investering i gründerbedrifter / oppstartsbedrifter - skatteinsentivordningen. Retrieved from https://www.skatteetaten.no/person/skatt/hjelp-til-riktig-skatt/aksjer-og-ver dipapirer/om/skatteinsentivordningen/

Statistics Norway. (2019). Newly established enterprises, survival and growth. Retrieved from https://www.ssb.no/virksomheter-foretak-og-regnskap/statistikker/fordem

Watson, J. & Everett, J. (1996). Small Business Failure Rates: Choice of Definition and the Size Effect. *International Small Business Journal*, 17(2), 31-47. Doi: 10.1177/0266242699172002

White, M. J. (1983). Bankruptcy Costs and the New Bankruptcy Code. *The Journal of Finance*, 38 (2), 477-488. Doi: 10.2307/2327983

Appendices

Appendix 1: Variables

Name	**Label**	**Type of Variable**	**Continuous /Dummy**	**Explanatory /Control**	**Formulas**
CEO gender	FEMALECEO	Independent	Dummy	Control	0 = Male 1 = Female
CEO age	CEOA	Independent	Continuous	Control	Fiscal year - CEO birth year
Firm Size	SIZE	Independent	Continuous	Control	Logarithm of Total Assets
Firm Age	AGE	Independent	Continuous	Control	Fiscal Year - the Founding Year
Growth	GROWTH	Independent	Continuous	Control	Change in the Natural Logarithm of Total Assets
Risk	RISK	Independent	Continuous	Control	Standard Deviation of Growth in Sales
Nature of Assets (Tangibility)	ITTA	Independent	Continuous	Explanatory	Intangibles to Total Assets
Financial Distress	financialdistress	Independent	Dummy	Control	0 = Non Financial distress 1 = Financial distress
Financial Ratios	See appendix 2.	Independent	Continuous	Explanatory	See appendix 2.
Bankruptcy, No Time Consideration	bankrupt	Dependent	Dummy		0 = Non-Bankrupt 1 = Bankrupt

Bankruptcy, with Time Consideration	bankrupt2	Dependent	Dummy		0 = Non-Bankrupt & Bankrupt Startups Before the Year of Bankruptcy 1= Bankrupt

Appendix 2: Financial Ratios

Name	Label	Type of variable	Continuous/ Dummy	Explanatory /Control	Formula
Liquidity Ratios					
Current Ratio	CUR	Independent	Continuous	Explanatory	$\frac{\text{Current Assets}}{\text{Current Liabilities}}$
Working Capital over Total Assets	WCOTA	Independent	Continuous	Explanatory	Working Capital / Total Assets
Cash to Current Liabilities	CTCL	Independent	Continuous	Explanatory	Cash & Cash Equivalents / Current Liabilities
Quick Assets to Total Assets	QATTA	Independent	Continuous	Explanatory	Quick Assets / Total Assets
Current Assets to Total Assets	CATTA	Independent	Continuous	Explanatory	Current Assets / Total Assets
Quick Ratio	QC	Independent	Continuous	Explanatory	Quick Assets / Current Liabilities
Activity/Efficiency Ratios					
Operating Income to Total Assets	OITTA	Independent	Continuous	Explanatory	Operating Income / Total Assets
Cash to Total Assets	CTTA	Independent	Continuous	Explanatory	Cash & Cash Equivalents / Total Assets

Profitability Ratios					
Return on Equity	ROE	Independent	Continuous	Control	$\frac{\text{Net Income}}{\text{Equity}}$
Return on Assets	ROA	Independent	Continuous	Control	Net Income / Total Assets
Retained Earnings to Total Assets	RETTA	Independent	Continuous	Explanatory	Retained Earnings / Total Assets
Solvency Ratios					
Total Debt to Total Assets	TDTTA	Independent	Continuous	Explanatory	Total Debt / Total Assets
Equity to Total Debt	ETTD	Independent	Continuous	Explanatory	Equity / Total Debt
Current Liabilities to Total Assets	CLTTA	Independent	Continuous	Explanatory	Current Liabilities / Total Assets
Long-Term Debt to Total Assets	LTDTTA	Independent	Continuous	Explanatory	Long-Term Debt / Total Assets
Total Debt to Equity	TDTE	Independent	Continuous	Explanatory	Total Debt / Equity

Appendix 3: Industries

Industries in italics are the ones that were removed as described under "Collection & Filtration of Data".

Alphabet Letter	Numeral letter	Name of Industry	Number of Observations
A	1	Agriculture, forestry, and fishing	9,508
B	*2*	*Mining and Quarrying*	*4,136*
C	3	Manufacturing	28,000
D	*4*	*Electricity, Gas, Steam, and Air Conditioning Supply*	*2,310*
E	5	Water Supply; Sewerage, Waste Management, and Remediation Activities	2,243
F	6	Construction	60,832
G	7	Wholesale and Retain Trade; Repair of Motor Vehicles and Motorcycles	91,151
H	8	Transportation and Storage	66,425
I	9	Accommodation and Food Service Activities	25,921
J	10	Information and Communication	30,949
K	*11*	*Financial and Insurance Activities*	*9,695*
L	12	Real Estate Activities	21,471
M	13	Professional, Scientific, and Technical Activities	122,306
N	14	Administrative and Support Service	22,980

		Activities	
O	*15*	*Public Administration and Defence; Compulsory Social Security*	*83*
P	16	Education	17,020
Q	17	Human Health and Social Work Activities	18,716
R	18	Arts, Entertainment, and Recreation	20,68
S	*19*	*Other Service Activities*	*12,117*
T	*20*	*Activities of Household as Employers; Undifferentiated Goods- and Services-Producing Activities of Households for Own Account*	*111*
U	*21*	*Activities of Extraterritorial Organizations and Bodies*	*2*
V	*22*	*Other*	*2,467*

TABLE 1: Data Description for Startups. 2000-2017.

This table reflect the data description for startups in the period 2000-2017. The data selection process are described under the section "data collection and filtration". At first, ROE, ROA, QC, WCOTA, RETTA, TDTTA, CTTA, QATTA, OITTA, LTDTTA, TDTE, CTCL, and ETTD were winsorized at 1 & 99 percentiles, and CUR, CLTTA, and RISK were only winsorized at 99 percentiles. Furthermore, RISK, CTCL, ETTD and QC was winsorized again at the 95 percentile, TDTE and ROE at 5 & 95 percentile, and at last RETTA at the 5 perccentile.

Panel 1: Both bankrupt and successful startups								
				Quantiles				
Variable	N	Mean	S.D.	Min	.25	Mdn	.75	Max
bankrupt2	537590	0.01	0.08	0.00	0.00	0.00	0.00	1.00
ROE	535708	0.48	0.98	-1.50	0.01	0.35	0.85	3.03
ROA	537590	-0.04	0.59	-3.79	-0.07	0.05	0.19	1.03
CUR	530246	2.17	3.75	0.00	0.87	1.25	1.96	29.40
QC	530246	1.46	1.36	0.02	0.59	1.08	1.71	5.64
WCOTA	537590	0.03	0.75	-4.76	-0.07	0.14	0.38	0.98
RETTA	537590	-0.04	0.55	-1.69	-0.13	0.05	0.25	0.87
TDTTA	537590	0.92	0.92	0.00	0.55	0.79	0.96	7.30
CATTA	537590	0.72	0.30	0.00	0.53	0.85	0.99	1.00
CTTA	537590	0.32	0.29	0.00	0.07	0.24	0.52	1.00
CLTTA	537590	0.69	0.75	0.00	0.31	0.57	0.84	5.57
QATTA	537590	0.61	0.33	0.01	0.33	0.66	0.93	1.00
OITTA	537590	0.01	0.58	-3.52	-0.06	0.07	0.25	1.18
LTDTTA	537590	0.20	0.34	0.00	0.00	0.00	0.29	1.82
TDTE	535708	2.43	6.37	-10.51	0.14	1.46	4.47	19.41
CTCL	530246	0.80	0.96	0.00	0.13	0.47	1.02	3.73
ETTD	532647	0.64	1.15	0.87	0.03	0.26	0.79	4.22
ITTA	537590	0.03	0.11	-1.16	0.00	0.00	0.00	2.55
financialdistress	537590	0.53	0.50	0.00	0.00	1.00	1.00	1.00
SIZE	537590	13.81	1.61	6.91	12.86	13.83	14.78	26.47
GROWTH	372773	0.01	0.05	-0.58	-0.01	0.00	0.02	1.20
RISK	435369	0.95	1.36	0.00	0.19	0.42	0.97	5.54
industryA	537590	0.02	0.13	0.00	0.00	0.00	0.00	1.00
industryC	537590	0.05	0.22	0.00	0.00	0.00	0.00	1.00
industryE	537590	0.00	0.06	0.00	0.00	0.00	0.00	1.00
industryF	537590	0.11	0.32	0.00	0.00	0.00	0.00	1.00
industryG	537590	0.17	0.38	0.00	0.00	0.00	0.00	1.00
industryH	537590	0.12	0.33	0.00	0.00	0.00	0.00	1.00
industryI	537590	0.05	0.21	0.00	0.00	0.00	0.00	1.00
industryJ	537590	0.06	0.23	0.00	0.00	0.00	0.00	1.00
industryL	537590	0.04	0.20	0.00	0.00	0.00	0.00	1.00
industryM	537590	0.23	0.42	0.00	0.00	0.00	0.00	1.00
industryN	537590	0.04	0.20	0.00	0.00	0.00	0.00	1.00
industryP	537590	0.03	0.18	0.00	0.00	0.00	0.00	1.00
industryQ	537590	0.03	0.18	0.00	0.00	0.00	0.00	1.00
industryR	537590	0.04	0.19	0.00	0.00	0.00	0.00	1.00
AGE	537590	2.80	1.88	0.00	1.00	3.00	4.00	6.00
FEMALECEO	475381	0.19	0.39	0.00	0.00	0.00	0.00	1.00
CEOA	475381	44.31	10.48	16.00	36.00	44.00	52.00	94.00

TABLE 1: Data Description for Startups. 2000-2017.

This table reflect the data description for bankrupt startups in the period 2000-2017. The data selection process are described under the section "data collection and filtration". At first, ROE, ROA, QC, WCOTA, RETTA, TDTTA, CTTA, QATTA, OITTA, LTDTTA, TDTE, CTCL, and ETTD were winsorized at 1 & 99 percentiles, and CUR, CLTTA, and RISK were only winsorized at 99 percentiles. Furthermore, RISK, CTCL, ETTD and QC was winsorized again at the 95 percentile, TDTE and ROE at 5 & 95 percentile, and at last RETTA at the 5 perccentile.

Panel 2: Bankrupt startups								
				Quantiles				
Variable	N	Mean	S.D.	Min	.25	Mdn	.75	Max
bankrupt2	3900	1.00	1.00	1.00	1.00	1.00	1.00	1.00
ROE	3889	0.53	1.14	-1.50	0.06	0.43	1.09	3.03
ROA	3900	-0.42	0.97	-3.79	-0.52	-0.10	0.08	1.03
CUR	3855	1.39	2.76	0.00	0.39	0.83	1.35	29.40
QC	3855	0.93	1.12	0.02	0.25	0.61	1.14	5.64
WCOTA	3900	-0.49	1.27	-4.76	-0.64	-0.11	0.19	0.98
RETTA	3900	-0.49	0.71	-1.69	-1.03	-0.24	0.03	0.87
TDTTA	3900	1.53	1.60	0.00	0.72	0.99	1.53	7.30
CATTA	3900	0.70	0.32	0.00	0.46	0.82	0.99	1.00
CTTA	3900	0.22	0.26	0.00	0.02	0.11	0.31	1.00
CLTTA	3900	1.19	1.28	0.00	0.47	0.82	1.28	5.57
QATTA	3900	0.57	0.34	0.01	0.26	0.57	0.92	1.00
OITTA	3900	-0.35	0.93	-3.52	-0.49	-0.08	0.12	1.18
LTDTTA	3900	0.24	0.43	0.00	0.00	0.00	0.33	1.82
TDTE	3889	0.64	6.90	-10.51	-2.78	0.00	2.65	19.41
CTCL	3855	0.36	0.65	0.00	0.02	0.12	0.39	3.73
ETTD	3873	0.22	1.03	-0.87	-0.35	0.00	0.38	4.22
ITTA	3900	0.04	0.12	-0.02	0.00	0.00	0.00	1.00
financialdistress	3900	0.81	0.39	0.00	1.00	1.00	1.00	1.00
SIZE	3900	13.18	1.62	6.91	12.26	13.28	14.20	22.46
GROWTH	2532	-0.00	0.08	-0.57	-0.03	-0.00	0.03	0.93
RISK	1416	1.22	1.58	0.00	0.26	0.57	1.33	5.54
industryA	3900	0.01	0.10	0.00	0.00	0.00	0.00	1.00
industryC	3900	0.04	0.21	0.00	0.00	0.00	0.00	1.00
industryE	3900	0.00	0.07	0.00	0.00	0.00	0.00	1.00
industryF	3900	0.11	0.31	0.00	0.00	0.00	0.00	1.00
industryG	3900	0.18	0.38	0.00	0.00	0.00	0.00	1.00
industryH	3900	0.17	0.38	0.00	0.00	0.00	0.00	1.00
industryI	3900	0.09	0.29	0.00	0.00	0.00	0.00	1.00
industryJ	3900	0.05	0.21	0.00	0.00	0.00	0.00	1.00
industryL	3900	0.03	0.16	0.00	0.00	0.00	0.00	1.00
industryM	3900	0.22	0.41	0.00	0.00	0.00	0.00	1.00
industryN	3900	0.04	0.19	0.00	0.00	0.00	0.00	1.00
industryP	3900	0.02	0.13	0.00	0.00	0.00	0.00	1.00
industryQ	3900	0.01	0.10	0.00	0.00	0.00	0.00	1.00
industryR	3900	0.03	0.18	0.00	0.00	0.00	0.00	1.00
AGE	3900	2.50	1.70	0.00	1.00	2.00	3.50	6.00
FEMALECEO	3281	0.14	0.35	0.00	0.00	0.00	0.00	1.00
CEOA	3281	41.75	10.42	18.00	34.00	41.00	49.00	86.00

TABLE 1: Data Description for Startups. 2000-2017.

This table reflect the data description for the non-bankrupt startups in the period 2000-2017. The data selection process are described under the section "data collection and filtration". At first, ROE, ROA, QC, WCOTA, RETTA, TDTTA, CTTA, QATTA, OITTA, LTDTTA, TDTE, CTCL, and ETTD were winsorized at 1 & 99 percentiles, and CUR, CLTTA, and RISK were only winsorized at 99 percentiles. Furthermore, RISK, CTCL, ETTD and QC was winsorized again at the 95 percentile, TDTE and ROE at 5 & 95 percentile, and at last RETTA at the 5 perccentile.

Panel 3: Non-bankrupt startups								
				Quantiles				
Variable	N	Mean	S.D.	Min	.25	Mdn	.75	Max
bankrupt2	533690	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ROE	531819	0.48	0.98	-1.50	0.02	0.35	0.85	3.03
ROA	533690	-0.04	0.58	-3.79	-0.07	0.05	0.19	1.03
CUR	526391	2.18	3.76	0.00	0.87	1.26	1.97	29.40
QC	516391	1.46	1.36	0.02	0.60	1.09	1.72	5.64
WCOTA	533690	0.03	0.75	-4.76	-0.07	0.14	0.38	0.98
RETTA	533690	-0.04	0.55	-1.69	-0.12	0.05	0.25	0.87
TDTTA	533690	0.92	0.91	0.00	0.55	0.79	0.96	7.30
CATTA	533690	0.73	0.30	0.00	0.53	0.85	0.99	1.00
CTTA	533690	0.32	0.29	0.00	0.07	0.25	0.52	1.00
CLTTA	533690	0.69	0.74	0.00	0.31	0.57	0.83	5.57
QATTA	533690	0.61	0.33	0.01	0.33	0.66	0.93	1.00
OITTA	533690	0.01	0.58	-3.52	-0.06	0.08	0.25	1.18
LTDTTA	533690	0.20	0.34	0.00	0.00	0.00	0.29	1.82
TDTE	531819	2.44	6.36	-10.51	0.15	1.47	4.48	19.41
CTCL	526391	0.80	0.96	0.00	0.13	0.47	1.03	3.73
ETTD	528774	0.64	1.15	-0.87	0.04	0.26	0.80	4.22
ITTA	533690	0.03	0.11	-1.16	0.00	0.00	0.00	2.55
financialdistress	533690	0.53	0.50	0.00	0.00	1.00	1.00	1.00
SIZE	533690	13.81	1.61	6.91	12.86	13.03	14.79	26.47
GROWTH	370241	0.01	0.05	-0.58	-0.01	0.00	0.02	1.20
RISK	433953	0.95	1.36	0.00	0.19	0.42	0.97	5.54
industryA	533690	0.02	0.13	0.00	0.00	0.00	0.00	1.00
industryC	533690	0.05	0.22	0.00	0.00	0.00	0.00	1.00
industryE	533690	0.00	0.06	0.00	0.00	0.00	0.00	1.00
industryF	533690	0.11	0.32	0.00	0.00	0.00	0.00	1.00
industryG	533690	0.17	0.38	0.00	0.00	0.00	0.00	1.00
industryH	533690	0.12	0.33	0.00	0.00	0.00	0.00	1.00
industryI	533690	0.05	0.21	0.00	0.00	0.00	0.00	1.00
industryJ	533690	0.06	0.23	0.00	0.00	0.00	0.00	1.00
industryL	533690	0.04	0.20	0.00	0.00	0.00	0.00	1.00
industryM	533690	0.23	0.42	0.00	0.00	0.00	0.00	1.00
industryN	533690	0.04	0.20	0.00	0.00	0.00	0.00	1.00
industryP	533690	0.03	0.18	0.00	0.00	0.00	0.00	1.00
industryQ	533690	0.04	0.18	0.00	0.00	0.00	0.00	1.00
industryR	533690	0.04	0.18	0.00	0.00	0.00	0.00	1.00
AGE	533690	2.80	1.88	0.00	1.00	3.00	4.00	6.00
FEMALECEO	472100	0.19	0.39	0.00	0.00	0.00	0.00	1.00
CEOA	472100	44.33	10.48	16.00	36.00	44.00	52.00	94.00

TABLE 2: Correlations between variables.
This table reflect the Pearson correlation for the variables used in this thesis.

	bankrupt2	AGE	SIZE	GROWTH	RISK	ITTA	financial-distress	FEMALE-CEO	CEOA	industry	ROE	ROA	CUR	QC	WCOTA	RETTA	TDTTA	CATTA	CTTA	CLTTA	QATTA	OITTA	LTDTTA	TDTE	CTCL	I
bankrupt2	1.0000																									
AGE	0.0119	1.0000																								
SIZE	-0.0175	0.1594	1.0000																							
GROWTH	-0.0138	-0.0912	0.2137	1.0000																						
RISK	0.0129	-0.0610	-0.0700	0.1271	1.0000																					
ITTA	0.0027	-0.0124	0.0007	-0.0552	0.0394	1.0000																				
financialdistress	0.0360	-0.0117	-0.2342	-0.1815	0.0898	0.1790	1.0000																			
FEMALECEO	-0.0083	-0.0166	-0.1098	-0.0207	-0.0351	0.0126	0.0386	1.0000																		
CEOA	-0.0130	0.1119	0.0207	-0.0394	-0.0141	-0.0136	-0.0475	-0.0678	1.0000																	
industry	-0.0113	-0.0030	-0.1186	0.0085	0.0440	0.0227	-0.0232	0.1638	0.0487	1.0000																
ROE	0.0012	-0.0435	0.0337	0.0967	-0.0079	-0.0556	-0.1685	-0.0140	-0.0277	0.0377	1.0000															
ROA	-0.0361	0.0269	0.2791	0.3719	-0.0881	-0.0818	-0.3738	-0.0202	0.0219	0.0310	0.0707	1.0000														
CUR	-0.0151	0.0418	0.0292	-0.0040	0.0592	-0.0602	-0.1419	-0.0146	0.0918	0.0569	-0.0831	0.0831	1.0000													
QC	-0.0246	0.0402	0.0436	0.0370	0.0389	-0.0948	-0.3294	-0.0529	0.1304	0.1555	-0.0913	0.1907	0.7137	1.0000												
WCOTA	-0.0480	0.0156	0.3211	0.2295	-0.0764	-0.1255	-0.3990	-0.0059	0.0466	0.0101	-0.0436	0.5413	0.3307	0.4848	1.0000											
RETTA	-0.0487	0.0151	0.3832	0.2125	-0.1156	-0.1600	-0.5398	-0.0631	0.0721	0.0351	-0.0152	0.5459	0.2321	0.4297	0.6932	1.0000										
TDTTA	0.0450	-0.0011	-0.3288	-0.2394	0.0809	0.0452	0.3426	0.0346	-0.0442	-0.0320	0.0428	-0.5822	-0.2243	-0.3756	-0.8623	-0.7475	1.0000									
CATTA	-0.0047	-0.0129	-0.1870	0.0432	-0.0303	-0.2697	-0.3024	0.0587	0.0190	-0.0209	0.0957	0.0576	0.1021	0.1497	0.2173	0.0735	-0.0153	1.0000								
CTTA	-0.0235	-0.0365	-0.2190	0.0152	-0.0084	-0.1430	-0.2943	0.0681	0.0789	0.2115	0.0884	0.1074	0.1435	0.3540	0.1814	0.1950	-0.1128	0.4680	1.0000							
CLTTA	0.0467	-0.0210	-0.3977	-0.2131	0.0647	0.0201	0.2822	0.0295	-0.0398	-0.0187	0.0825	-0.5223	-0.2937	-0.4303	-0.9215	-0.6707	0.8625	0.1772	0.0019	1.0000						
QATTA	-0.0058	-0.0286	-0.2166	0.0576	0.0113	-0.2056	-0.3138	-0.0543	0.0572	0.1692	0.1149	0.0847	0.0893	0.3489	0.1590	0.1437	-0.0555	0.7303	0.6363	0.1286	1.0000					
OITTA	-0.0328	0.0257	0.2639	0.3490	-0.0897	-0.1134	-0.3948	-0.0243	0.0201	0.0358	0.1095	0.9607	0.0634	0.1774	0.5035	0.5214	-0.5257	0.0759	0.1218	-0.4768	0.1027	1.0000				
LTDTTA	0.0101	0.0269	0.1180	-0.0621	0.0375	0.0836	0.2404	0.0235	-0.0369	-0.0517	-0.0529	-0.1815	0.0504	-0.0396	-0.0701	-0.3372	0.3496	-0.4418	-0.3205	-0.1060	-0.4523	-0.1623	1.0000			
TDTE	-0.0180	0.0022	0.1967	0.0889	-0.0395	-0.0542	-0.0989	-0.0244	-0.0157	-0.0012	-0.0506	0.1384	-0.0418	-0.0540	0.1128	0.1707	-0.1178	-0.0141	-0.0260	-0.1195	-0.0134	0.1373	-0.0161	1.0000		
CTCL	-0.0289	0.0207	-0.0098	0.0196	0.0188	-0.0840	-0.3078	0.0170	0.1307	0.1760	-0.0681	0.1690	0.6046	0.8439	0.4087	0.3831	-0.3263	0.1276	0.6115	-0.3623	0.2845	0.1614	-0.0613	-0.0607	1.0000	
ETTD	-0.0254	0.0478	0.0387	0.0246	0.0098	-0.0630	-0.3337	-0.0349	0.1301	0.1257	-0.1336	0.2444	0.5103	0.7418	0.4893	0.5737	-0.5274	0.0928	0.2827	-0.4575	0.1893	0.2224	-0.3287	-0.0937	0.6706	1

TABLE 3: Selection of Variables

Table 3 presents the outcome from the selection of variables. Variables were removed from which had the highest p-value, until the model was significant (marked with a line). The table must be read from the bottom up, where column (1) - (3) reflects results from a one variable logit regression, while column (4) - (6) reflect the logit with all parameters in line with the reported numbers and above. The p-value reported in column (4) is for the respective variable within the model. The variables above the marked line are the model which includes all the significant variables.

Bankrupt2 as Dependent Variable						
Factor	**Coefficient Estimate (1)**	**z-stat (2)**	**Own R2 (3)**	**P-value (4)**	**Pseudo R2 (5)**	**AIC (6)**
2.AGE	0.4316908	11.51	0.0027	0.000	0.0641	14385.80
3.AGE	0.1754076	4.17	0.0004	0.017	0.0641	14385.80
4.AGE	-0.3610525	-6.78	0.0011	0.000	0.0641	14385.80
5.AGE	-0.7906930	-11.68	0.0037	0.000	0.0641	14385.80
RISK	0.1199414	7.39	0.0026	0.000	0.0641	14385.80
ITTA	0.4137354	3.06	0.0002	0.024	0.0641	14385.80
financialdistress	1.3539990	33.03	0.0298	0.000	0.0641	14385.80
FEMALECEO	-0.3864082	-7.63	0.0016	0.000	0.0641	14385.80
CEOA	-0.0244478	-14.02	0.0052	0.000	0.0641	14385.80
RETTA	-0.9905250	-47.69	0.0414	0.000	0.0641	14385.80
CTTA	-1.5757060	-22.78	0.0132	0.000	0.0641	14385.80
CLTTA	0.4252748	38.47	0.0216	0.000	0.0641	14385.80
QATTA	-0.4109615	-8.46	0.0015	0.000	0.0641	14385.80
TDTE	-0.0483868	-17.65	0.0071	0.000	0.0641	14385.80
CTCL	-0.9831463	-27.05	0.0270	0.000	0.0641	14385.80
ETTD	-0.5340888	-22.33	0.0155	0.007	0.0641	14385.80
ROA	-0.5426480	-37.67	0.0210	0.138	0.0642	14385.61
TDTTA	0.3222865	37.44	0.0202	0.070	0.0644	14384.10
LTDTTA	0.3550447	8.61	0.0015	0.116	0.0646	14383.66
ROE	0.0575259	3.58	0.0003	0.200	0.0647	14384.03
OITTA	-0.5567462	-36.26	0.0200	0.297	0.0648	14617.63
CUR	-0.1614551	-12.76	0.0068	0.495	0.0648	14386.53
QC	-0.4767323	-23.36	0.0172	0.494	0.0648	14641.82
SIZE	-0.2350447	-24.72	0.0126	0.559	0.0649	14654.05
GROWTH	-3.8189780	-10.94	0.0036	0.654	0.0660	14233.14
CATTA	-0.2940922	-5.72	0.0007	0.671	0.0661	14234.96
WCOTA	-0.4448203	-40.44	0.0239	0.697	0.0661	14236.81

TABLE 4: Selection of Variables with Clustered Standard Errors

Table 5 presents the outcome from the selection of robust variables. Variables were removed from which had the highest p-value, until the model was significant (marked with a line). The table must be read from the bottom up, where column (1) - (3) reflects results from a one variable logit regression, while column (4) - (6) reflect the logit with all parameters in line with the reported numbers and above. The p-value reported in column (4) is for the respective variable within the model. The variables above the marked line are the model which includes all the significant variables. The standard errors were clustered at industry level.

Bankruptcy2 as Dependent Variable						
Factor	Coefficient Estimate (1)	z-stat (2)	Own pseudo R2 (3)	P-value (4)	Pseudo R2 (5)	AIC (6)
2.AGE	0.4316908	7.68	0.0027	0.000	0.0642	14375.42
3.AGE	0.1754076	3.96	0.0004	0.009	0.0642	14375.42
4.AGE	-0.3610525	-3.73	0.0011	0.000	0.0642	14375.42
5.AGE	-0.7906930	-5.66	0.0037	0.000	0.0642	14375.42
RISK	0.1199414	4.29	0.0026	0.011	0.0642	14375.42
ITTA	0.4137354	3.15	0.0002	0.004	0.0642	14375.42
financialdistress	1.3539990	17.91	0.0298	0.000	0.0642	14375.42
FEMALECEO	-0.3864082	-3.80	0.0016	0.000	0.0642	14375.42
CEOA	-0.0244478	-6.68	0.0052	0.000	0.0642	14375.42
RETTA	-0.9905250	-23.33	0.0414	0.000	0.0642	14375.42
TDTTA	0.3222865	28.62	0.0202	0.010	0.0642	14375.42
CTTA	-1.5757060	-7.16	0.0132	0.000	0.0642	14375.42
CLTTA	0.4252748	29.40	0.0216	0.000	0.0642	14375.42
QATTA	-0.4109615	-2.52	0.0015	0.002	0.0642	14375.42
TDTE	-0.0483868	-11.95	0.0071	0.000	0.0642	14375.42
CTCL	-0.9831463	-11.62	0.0270	0.000	0.0642	14375.42
ETTD	-0.5340888	-8.12	0.0155	0.009	0.0642	14375.42
ROA	-0.5426480	-24.52	0.0210	0.077	0.0644	14372.10
LTDTTA	0.3550447	3.84	0.0015	0.155	0.0646	14369.66
OITTA	-0.5567462	-21.31	0.0200	0.242	0.0647	14368.57
CATTA	-0.2940922	-1.52	0.0007	0.562	0.0647	14368.20
WCOTA	-0.4448203	-29.59	0.0239	0.319	0.0647	14367.93
ROE	0.0575259	2.28	0.0003	0.356	0.0648	14366.44
CUR	-0.1614551	-4.06	0.0068	0.621	0.0648	14366.09
QC	-0.4767323	-10.04	0.0172	0.547	0.0649	14365.75
SIZE	-0.2350447	-8.28	0.0126	0.713	0.0649	14365.41
GROWTH	-3.8189780	-6.18	0.0036	0.706	0.0661	14206.81

TABLE 5: Selection of Variables with Clustered Standard Errors - Robustness test

Table 6 presents the outcome from the robustness test. The variables were removed according to the lowest z-statistics to find the model with lowest AIC. The table must be read from the bottom-up, where the columns (4)-(6) reflects the model that includes the variable that is in line with the reported numbers as well as all the variables above. Columns (1)-(3) reflects the results from a one-variable logit. The standard errors were clustered at the industry level.

Bankruptcy2 as Dependent Variable						
Factor	Coefficient Estimate (1)	Own z-stat (2)	Own pseudo R2 (3)	z-stat (4)	Pseudo R2 (5)	AIC (6)
CLTTA	0.4252748	29.40	0.0216	29.40	0.0216	45200.21
financialdistress	1.3539990	17.91	0.0298	16.54	0.0414	44290.97
3.AGE	0.1754076	3.96	0.0004	4.49	0.0436	44193.46
RISK	0.1199414	4.29	0.0026	2.98	0.0428	17455.18
QATTA	-0.4109615	-2.52	0.0015	0.49	0.0429	17456.44
TDTTA	0.3222865	28.62	0.0202	0.02	0.0429	17458.44
2.AGE	0.4316908	7.68	0.0027	-1.36	0.0431	17456.09
ITTA	0.4137354	3.15	0.0002	-1.63	0.0433	17455.73
4.AGE	-0.3610525	-3.73	0.0011	-1.61	0.0434	17454.45
ETTD	-0.5340888	-8.12	0.0155	-4.23	0.0448	17352.5
FEMALECEO	-0.3864082	-3.80	0.0016	-4.32	0.0458	14710.64
CTCL	-0.9831463	-11.62	0.0270	-6.87	0.0516	14584.83
CTTA	-1.5757060	-7.16	0.0132	-4.23	0.0533	14559.49
RETTA	-0.9905250	-23.33	0.0414	-5.32	0.0568	14505.95
TDTE	-0.0483868	-11.95	0.0071	-4.97	0.0582	14468.46
5.AGE	-0.7906930	-5.66	0.0037	-5.70	0.0613	14419.75
CEOA	-0.0244478	-6.68	0.0052	-6.84	0.0642	14375.42

TABLE 6: Variables' performance under various circumstances for startups. 2001-2017.

Table 6 presents the outcome from the different robustness tests with bankrupt variable that is 1 when bankrupt and 0 when non-bankrupt as dependent variable. This bankrupt variable does not take time into consideration. The debt ratios reflect a book-based definition of leverage. The robust, core factors are marked in bold. Three different groups were tested: (1) high and low growth, (2) large and small firms, and (3) high and low tangibility. The levels of high and low were seen in perspective with the 66th and 33rd percentile in annual cross-sections. Therefore, the startup was classed as high growth, if the change in the log of assets surpassed the 66th percentile. Respectively, a classification of a low growth startup followed for a change in the log of assets below the 33rd percentile. A startup was considered of great size if the log of total assets exceeded the 66th percentile, and classified as small if the log of total assets were under the 33rd percentile. Lastly, a startup was acknowledged with high tangibility if the ratio of tangible assets to total fixed assets surpassed the 66th percentile. Respectively, if the tangibility ratio was below the 33rd percentile, then the startup was classified with low tangibility. The variables marked in bold are considered core variables that passed the robustness test. The standard errors were clustered at the industry level. The data selection process for these variables is described under the section "Data Collection and Filtration". The definition of the various variables is found in Appendix 1.

	Bankruptcy as dependent variable											
Factor	High Growth		Low growth		Large firms		Small firms		High tangibility		Low Tangibility	
	+ %	- %	+ %	- %	+ %	- %	+ %	- %	+ %	- %	+ %	- %
FEMALECEO	0,00 %	23,53 %	0,00 %	23,53 %	11,76 %	0,00 %	0,00 %	17,65 %	0,00 %	17,65 %	0,00 %	23,53 %
CEOA	0,00 %	35,29 %	0,00 %	29,41 %	5,88 %	23,53 %	0,00 %	17,65 %	0,00 %	41,18 %	0,00 %	47,06 %
SIZE	29,41 %	47,06 %	29,41 %	23,53 %	0,00 %	52,94 %	35,29 %	17,65 %	23,53 %	41,18 %	29,41 %	29,41 %
1.AGE	17,65 %	0,00 %	23,53 %	0,00 %	41,18 %	0,00 %	23,53 %	0,00 %	35,29 %	0,00 %	47,06 %	0,00 %
2.AGE	35,29 %	0,00 %	41,18 %	0,00 %	58,82 %	5,88 %	35,29 %	0,00 %	58,82 %	0,00 %	47,06 %	0,00 %
3.AGE	29,41 %	0,00 %	41,18 %	5,88 %	47,06 %	0,00 %	35,29 %	0,00 %	47,06 %	5,88 %	41,18 %	5,88 %
4.AGE	23,53 %	35,29 %	23,53 %	17,65 %	17,65 %	5,88 %	17,65 %	11,76 %	5,88 %	0,00 %	17,65 %	11,76 %
5.AGE	11,76 %	23,53 %	5,88 %	17,65 %	11,76 %	5,88 %	0,00 %	0,00 %	5,88 %	5,88 %	5,88 %	17,65 %
6.AGE	0,00 %	17,65 %	0,00 %	17,65 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
GROWTH	35,29 %	0,00 %	0,00 %	17,65 %	35,29 %	0,00 %	17,65 %	17,65 %	23,53 %	0,00 %	17,65 %	0,00 %
RISK	11,76 %	0,00 %	5,88 %	11,76 %	17,65 %	0,00 %	23,53 %	0,00 %	11,76 %	0,00 %	11,76 %	5,88 %
ITTA	0,00 %	11,76 %	11,76 %	0,00 %	0,00 %	23,53 %	5,88 %	0,00 %	11,76 %	5,88 %	0,00 %	0,00 %
financialdistress	47,06 %	0,00 %	52,94 %	0,00 %	29,41 %	0,00 %	58,82 %	0,00 %	29,41 %	0,00 %	64,71 %	0,00 %
CUR	17,65 %	29,41 %	5,88 %	17,65 %	17,65 %	11,76 %	17,65 %	11,76 %	11,76 %	29,41 %	17,65 %	17,65 %
WCOTA	35,29 %	5,88 %	11,76 %	35,29 %	11,76 %	17,65 %	5,88 %	23,53 %	23,53 %	35,29 %	0,00 %	41,18 %
CTCL	11,76 %	11,76 %	5,88 %	17,65 %	5,88 %	23,53 %	0,00 %	17,65 %	0,00 %	29,41 %	5,88 %	17,65 %
QATTA	11,76 %	5,88 %	17,65 %	11,76 %	23,53 %	0,00 %	29,41 %	0,00 %	11,76 %	5,88 %	41,18 %	0,00 %
CATTA	5,88 %	17,65 %	17,65 %	0,00 %	23,53 %	11,76 %	0,00 %	11,76 %	23,53 %	17,65 %	11,76 %	0,00 %
OITTA	29,41 %	5,88 %	17,65 %	0,00 %	11,76 %	41,18 %	17,65 %	5,88 %	11,76 %	5,88 %	0,00 %	5,88 %
CTTA	0,00 %	52,94 %	0,00 %	47,06 %	0,00 %	47,06 %	0,00 %	41,18 %	0,00 %	35,29 %	0,00 %	58,82 %
ROE	17,65 %	5,88 %	17,65 %	29,41 %	11,76 %	0,00 %	11,76 %	0,00 %	5,88 %	11,76 %	11,76 %	5,88 %
ROA	5,88 %	29,41 %	0,00 %	11,76 %	17,65 %	11,76 %	5,88 %	17,65 %	0,00 %	17,65 %	5,88 %	17,65 %
RETTA	17,65 %	5,88 %	5,88 %	5,88 %	17,65 %	17,65 %	0,00 %	29,41 %	5,88 %	5,88 %	11,76 %	0,00 %
TDTTA	11,76 %	41,18 %	0,00 %	17,65 %	5,88 %	23,53 %	0,00 %	23,53 %	5,88 %	52,94 %	11,76 %	17,65 %
ETTD	5,88 %	0,00 %	0,00 %	5,88 %	11,76 %	0,00 %	11,76 %	5,88 %	11,76 %	0,00 %	17,65 %	5,88 %
CLTTA	82,35 %	0,00 %	47,06 %	0,00 %	47,06 %	11,76 %	29,41 %	0,00 %	47,06 %	0,00 %	11,76 %	0,00 %
LTDTTA	23,53 %	0,00 %	23,53 %	0,00 %	29,41 %	0,00 %	23,53 %	11,76 %	41,18 %	0,00 %	11,76 %	5,88 %
QC	23,53 %	23,53 %	17,65 %	5,88 %	5,88 %	17,65 %	5,88 %	5,88 %	11,76 %	5,88 %	0,00 %	11,76 %
TDTE	5,88 %	5,88 %	0,00 %	29,41 %	0,00 %	17,65 %	0,00 %	11,76 %	0,00 %	17,65 %	5,88 %	17,65 %

TABLE 7: Core Logistic Regression Model

Table 7 presents the core variables in a logistic regression model that is clustered at industry. It consists of 8 control variables (2.AGE, 3.AGE, 4.AGE, 5.AGE, RISK, financialdistress, FEMALECEO, CEOA), and 9 explanatory variables (ITTA, RETTA, TDTTA, CTTA, CLTTA, QATTA, TDTE, CTCL, and ETTD).

Bankrutpcy2 as Dependent Variable

Logistic regression	Number of obs	=	**288,618**
	Wald chi2(12)	=	**.**
	Prob > chi2	=	**.**
Log pseudolikelihood = **-7174.709**	Pseudo R2	=	**0.0642**

(Std. Err. Adjusted for **14** clusters in industry)

bankrupt2	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AGE						
2	-.541054	.1292716	-4.19	0.000	-.7944218	-.2876863
3	-.2098164	.0805037	-2.61	0.009	-.3676007	-.052032
4	-.5410595	.1121004	-4.83	0.000	-.7607722	-.3213468
5	-.7464613	.1276631	-5.85	0.000	-.9966763	-.4962463
RISK	.0799727	.0314795	2.54	0.011	.0182741	.1416713
ITTA	-.6457804	.224643	-2.87	0.004	-1.086073	-.2054883
nancialdistress	.7567888	.0904748	8.36	0.000	.5794614	.9341162
FEMALECEO	-.3936551	.0873867	-4.50	0.000	-.56493	-.2223803
CEOA	-.0197064	.0028808	-6.84	0.000	-.0253527	-.01406
RETTA	-.4453516	.0927658	-4.80	0.000	-.6271692	-.263534
TDTTA	-.0817344	.0317274	-2.58	0.010	-.143919	-.0195499
CTTA	-.8021585	.2026758	-3.96	0.000	-1.199396	-.4049213
CLTTA	.2342575	.0402657	5.82	0.000	.1553381	.3131769
QATTA	.4726748	.1500582	3.15	0.002	.1785661	.7667835
TDTE	-.0208232	.0041715	-4.99	0.000	-.0289991	-.0126473
CTCL	-.3753558	.0857402	-4.38	0.000	-.5434035	-.2073081
ETTD	.1079357	.0415183	2.60	0.009	.0265613	.1893101
_cons	-4.811027	.2061065	-23.34	0.000	-5.214989	-4.407066

TABLE 8: Goodness of Fit

Table 8 presents whether the expected event rates in subgroups of

Goodness of fit test: Core model

Logistic model for bankrupt, godness-of-fit test

(Table collapes on quantiles of estimated probabilities)

Number of observations =	288618
Number of groups =	10
Homser-Lemeshow chi2(8) =	8 .87
Prob > chi2 =	0 .3538

TABLE 9: Classification Test - Core Model

Table 9 presents the classifications of the core model

Classification test: Core model

Logistic model for bankrupt2

Classified	------- True ------- D	~D	Total
+	**835**	**93531**	**94366**
-	**345**	**193907**	**194252**
Total	**1180**	**287438**	**288618**

Classified + if predicted Pr(D) >= .0040885

True D defined as bankrupt != 0

Sensitivity	Pr(+| D)	**70.76%**
Specificity	Pr(-|~D)	**67.46%**
Positive predictive value	Pr(D| +)	**0.88%**
Negative predictive value	Pr(~D| -)	**99.82%**
False + rate for true ~D	Pr(+|~D)	**32.54%**
False - rate for true D	Pr(- | D)	**29.24%**
False + rate for classified +	Pr(~D| +)	**99.12%**
False - rate for classified -	Pr(D| -)	**0.18%**
Correctly classified		**67.47%**

TABLE 10: Logistic Regression Core Model in Period 2000 - 2005

Table 10 presents the core variables in a logistic regression model that is clustered at industry for the period before the tax-reform. It consists of 8 control variables (2.AGE, 3.AGE, 4.AGE, 5.AGE, RISK, financialdistress, FEMALECEO, CEOA), and 9 explanatory variables (ITTA, RETTA, TDTTA, CTTA, CLTTA, QATTA, TDTE, CTCL, and ETTD).

Bankrupt2 as Dependent Variable

Logistic regression	Number of obs	=	**66,258**
	Wald chi2(11)	=	**.**
	Prob > chi2	=	**.**
Log pseudolikelihood = **-1187.6143**	Pseudo R2	=	**0.1040**

(Std. Err. Adjusted for **13** clusters in industry)

bankrupt2	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AGE						
2	-.3645962	.2086522	-1.75	0.081	-.773547	.0443546
3	.4199665	.1710701	2.45	0.014	.0846753	.7552578
4	-.1119402	.1968855	-0.57	0.570	.4978287	.2739482
5	-.8705484	.1358649	-6.41	0.000	1.136839	-.6042581
RISK	.0290470	.0641061	0.45	0.650	.0965985	.1546926
ITTA	-.2099790	.8600372	-0.24	0.807	1.895621	1.475663
nancialdistress	1.211103	.1754486	6.90	0.000	.8672306	1.554976
FEMALECEO	-.6082477	.1912546	-3.18	0.001	.9830998	-.2333955
CEOA	-.0270544	.0887485	-3.09	0.002	.0442011	-.0099077
RETTA	-.8534406	.2294621	-3.72	0.000	1.303178	-.4037030
TDTTA	-.0709271	.2154606	-0.33	0.742	.4932222	.3513679
CTTA	-.0713413	.4029265	-0.18	0.859	.8610627	.7183802
CLTTA	.2996427	.2232547	1.34	0.180	.1379285	.7372139
QATTA	.0239347	.2248838	0.11	0.915	.4168295	.4646988
TDTE	-.0245937	.0192199	-1.28	0.201	.0622639	.0130765
CTCL	-.3370962	.1916507	-1.76	0.079	.7127247	.0385323
ETTD	.2445823	.1383613	1.77	0.077	.0266009	.5157655
_cons	-5.780885	.3898577	-14.83	0.000	6.544992	-5.016778

TABLE 11: Logistic Regression Core Model in Period 2006 - 2017

Table 11 presents the core variables in a logistic regression model that is clustered at industry for the period after the tax-reform. It consists of 8 control variables (2.AGE, 3.AGE, 4.AGE, 5.AGE, RISK, financialdistress, FEMALECEO, CEOA), and 9 explanatory variables (ITTA, RETTA, TDTTA, CTTA, CLTTA, QATTA, TDTE, CTCL, and ETTD).

Bankrupt2 as Dependent Variable

Logistic regression	Number of obs	=	**222,360**
	Wald chi2(12)	=	**.**
	Prob > chi2	=	**.**
Log pseudolikelihood = **-5934.6261**	Pseudo R2	=	**0.0619**

(Std. Err. Adjusted for **14** clusters in industry)

bankrupt2	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AGE						
2	-.5627971	.1320682	-4.26	0.000	.8216461	-.3039481
3	-.3223783	.0822656	-3.92	0.000	.4836158	-.1611407
4	-.5958833	.1338926	-4.45	0.000	.8583081	-.3334586
5	-.7153264	.1331310	-5.37	0.000	.9762583	-.4543945
RISK	.0719708	.0330006	2.18	0.029	.0072908	.1366507
ITTA	-.7252902	.2423812	-2.99	0.003	1.200349	-.2502319
nancialdistress	.6887302	.0897082	7.68	0.000	.5129054	.8645550
FEMALECEO	-.3894501	.1003032	-3.88	0.000	.5860408	-.1928594
CEOA	-.0199067	.0025332	-7.86	0.000	.0248718	-.0149416
RETTA	-.3708367	.0864703	-4.29	0.000	.5403154	-.2013581
TDTTA	-.0914931	.0467194	-1.96	0.050	.1830615	.0000752
CTTA	-.9310603	.2608038	-3.57	0.000	1.442226	-.4198943
CLTTA	.2166258	.0760495	2.85	0.004	.0675714	.3656801
QATTA	.5159445	.1256672	4.11	0.000	.2696413	.7622477
TDTE	-.0163570	.0043842	-3.73	0.000	.0249498	-.0077641
CTCL	-.3991075	.1059909	-3.77	0.000	.6068458	-.1913692
ETTD	.0510229	.0575512	0.89	0.375	.0617754	.1638212
_cons	-4.506252	.2008395	-22.44	0.000	4.899891	-4.112614

TABLE 12: Logistic Regression Core Model with Industry Variables

Table 12 presents the core variables with the addition of industry variables in a logistic regression model that is *not* clustered at industry. It consists of 21 control variables (2.AGE, 3.AGE, 4.AGE, 5.AGE, all industry-variables, RISK, financialdistress, FEMALECEO, CEOA), and 9 explanatory variables (ITTA, RETTA, TDTTA, CTTA, CLTTA, QATTA, TDTE, CTCL, and ETTD).

Bankrupt2 as Dependent Variable

Logistic regression	Number of obs	=	**288,618**
	Wald chi2(12)	=	**1084.72**
	Prob > chi2	=	**0.0000**
Log likelihood = **-7124.7394**	Pseudo R2	=	**0.0707**

bankrupt2	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
AGE						
2	-.5435192	.0923133	-5.89	0.000	-.72445	-.3625883
3	-.2085305	.0864711	-2.41	0.016	-.3780108	-.0390503
4	-.5390829	.0953246	-5.66	0.000	-.7259157	-.3522501
5	-.7457794	.1067073	-6.99	0.000	-.9549218	-.536637
industry						
3	.5028299	.3616514	1.39	0.164	-.2059938	1.211654
5	.9613795	.5292991	1.82	0.069	-.0760277	1.998787
6	1.071197	.3425858	3.13	0.002	.3997412	1.742653
7	.8974921	.3406741	2.63	0.008	.2297831	1.565201
8	.9165267	.3431465	2.67	0.008	.2439719	1.589081
9	1.35169	.3484772	3.88	0.000	.6686873	2.034693
10	.5876273	.3582205	1.64	0.101	-.114472	1.289727
12	.465807	.3925094	1.19	0.235	-.3034974	1.235111
13	.4360086	.3440584	1.27	0.205	-.2383335	1.110351
14	.7970288	.3632292	2.19	0.028	.0851127	1.508945
16	.4450883	.400498	1.11	0.266	-.3398734	1.23005
17	.1311543	.4246427	0.31	0.757	-.7011301	.9634388
18	.4819237	.3806798	1.27	0.206	-.2641949	1.228042
RISK	.0937543	.0187443	5.00	0.000	.0570163	.1304924
ITTA	-.4324157	.2770736	-1.56	0.119	-.97547	.1106386
nancialdistress	.7711889	.0865891	8.91	0.000	.6014774	.9409004
FEMALECEO	-.3509396	.0865037	-4.06	0.000	-.5204837	-.1813955
CEOA	-.0170751	.0029998	-5.69	0.000	-.0229547	-.0111955
RETTA	-.4504523	.0696175	-6.47	0.000	-.5869	-.3140045
TDTTA	-.0584054	.0538887	-1.08	0.278	-.1640254	.0472146
CTTA	-.8368759	.181966	-4.60	0.000	-1.193523	-.480229
CLTTA	.2046708	.0661254	3.10	0.002	.0750674	.3342743
QATTA	.6042172	.1176323	5.14	0.000	.3736622	.8347722
TDTE	-.0191031	.0048095	-3.97	0.000	-.0285296	-.0096767
CTCL	-.3621806	.0826817	-4.38	0.000	-.5242337	-.2001274
ETTD	.1449857	.046936	3.09	0.002	.0529929	.2369786
_cons	-5.829167	.3776758	-15.43	0.000	-6.569398	-5.088936

FIGURE 1: Cutoff for Classification: Core Model

Figure 1 was used to check where the sensitivity/specificity lines cross for the cutoff to estimate the classification test correctly.

Cutoff for classification: core model

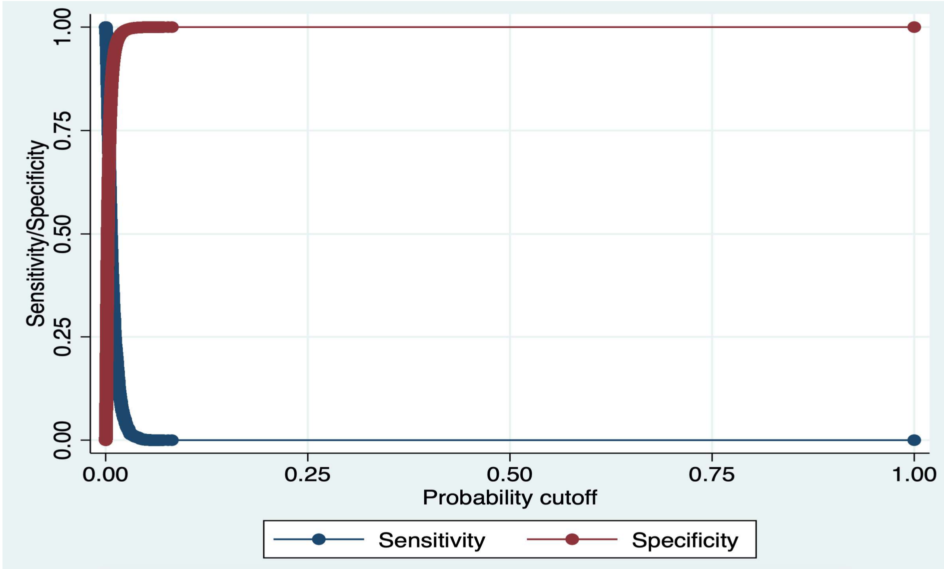
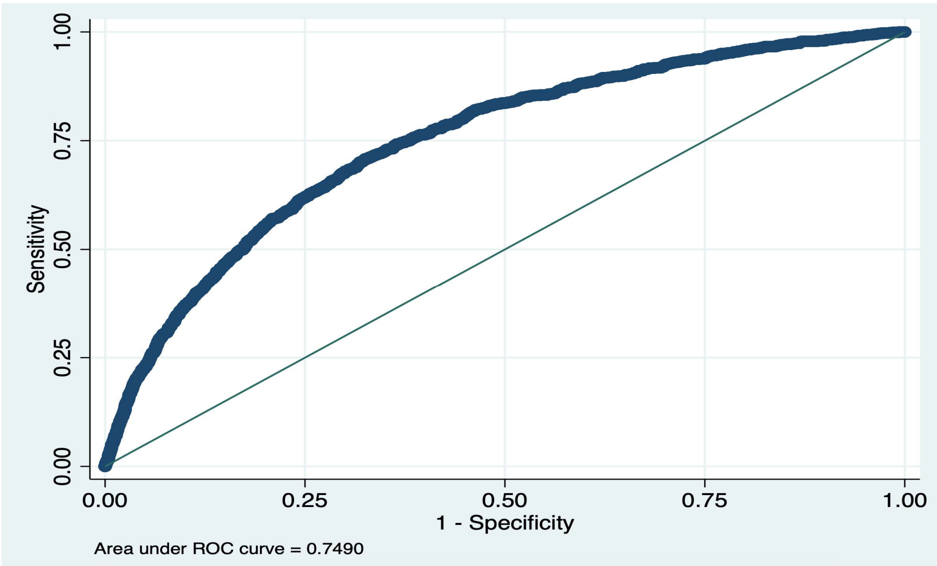


FIGURE 2: ROC Curve - Core Model

Figure 2 presents the ROC curve and the area under ROC curve, which shows how well a parameter can distinguish between two groups (bankrupt/non-bankrupt in this case, with a time restriction that bankrupt follows the year of bankruptcy)

ROC-curve: Core model



BI Norwegian Business School - campus Oslo

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Master Thesis

Preliminary thesis report

What are, if any, the explanatory financial factors of bankruptcy in Norwegian startups?

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What are, if any, the explanatory financial factors of bankruptcy in Norwegian startups?

MSC IN BUSINESS,
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1 INTRODUCTION

In our thesis, we will look into startups and mainly why most of them go bankrupt within four to five years, even if they have shown signs of being successful or not. It is necessary to mention that we will disregard those startups who have been operating one to three years before going bankrupt since other factors could strongly influence the bankruptcy as well as there will not be satisfactory enough accounting information.

There are different ways to study the bankruptcy of a startup, and both quantitative and qualitative methods work. In our literature review, we have studied which two of these methods that have previously influenced the literature. Moreover, the focus in previous literature shows that the biggest interest has been to find out which factors that have influenced the success through using a qualitative method.

The research shows that often factors like poor management, wrong product, already satisfied market, wrong timing, etc. is common factors for why startups in general disappear. Moreover, most of the research focuses on these factors. Furthermore, the entrepreneur may also be experiencing rapid growth in the business which might result in too much to handle for the inexperienced entrepreneur. In the book *Why Startups Fail,* David Feinleib has four aspects that could be the underlying reason for failure:

1. Market, Product, and Entrepreneur,
2. Sales and Marketing,
3. Execution,
4. Capital and Liquidity.

The four categories are based on Feinleib's own experiences from Microsoft, Hewlett-Packard, and venture-capital firms. He brings real-life experiences into the literature field about startups, which differs from other publications that use research and academic perspective.

There is increasing interest in the importance of supporting startups with actors like DnB, Innovation Norway and StartupLab playing a key role in the knowledge sharing between the parties. For Norwegian startups, only 27% survive after five years of business (Hvamstad, 2017). Therefore, there is a lot of information to be retrieved from those who go bankrupt. There is a lot of studies that point out that there are strategic factors behind a startup failure, and the knowledge gap within this research area is the use of financial statements and quantitative methods alone to explain a startup bankruptcy. Thus, this has resulted in interest for us to find out if it is possible to find a common denominator among those who go bankrupt after four to five years by looking at their accounting information. This interest resulted in our current research question:

> *What are, if any, the explanatory financial factors of bankruptcy in Norwegian startups?*

We would like to point out that the research question might be subject to a slight change in formulation.

We will first start by retrieving the data from the Centre for Corporate Governance Research (CCGR) database, where we will clean the data and set it up to conduct our wished models. Whether we separate between markets or look at a total, will we decide upon once we have cleaned the data. Before making the regression model, we want to examine different financial ratios to analyse the situation. Thereafter, we will use our model to hopefully get reasonable results. We might do some slight adjustments to the model, and perhaps also adjust for different types of risk if we find it necessary. Finally, we will analyse the results from the data and see if there are any relationship and similarities between the different results.

2 BACKGROUND

A startup is “a new business, or the activities involved in starting a new business” (Cambridge, 2020). In 2017, there were 62 000 new companies established in Norway, which is an increase of 3% from 2016 (Holm, 2018). Some important factors that startups bring to the business environment, is the creation of new jobs and solving potential problems that may be in the business environment. Companies like DnB, Telia, BDO, and Equinor assist startups in their everyday business to help them become more successful. Moreover, Innovation Norway is created by the

Parliament of Norway to help assist Norwegian startups to handle both local and global challenges as well as support some with funding.

It is important to study startups and their success/mistakes since it provides a lot of information. It is hard to make one solid explanation for why bankruptcy occurs since it often changes between each bankruptcy. Therefore, the reason for startup bankruptcy is complex and a lot of factors is in play. Moreover, the research of this topic strongly focuses on the successes and or how different strategic, human, etc., factors have played a role in the disappearance of the firm. The assistance from banks and companies who handle similar issues every day provides important knowledge transfer for the startup firms.

To contribute to this research field, we want to look at how for instance the balance sheet and income statement could be a useful tool to predict a possible future bankruptcy. The balance sheet is important to analyse since it gives an overview of the company's financial situation at a given time, which describes the assets on one side and the debt and equity on the other (Visma, 2020). Also, the income statement is important since it shows the total income and expenses for a company during a year (Visma, 2020). Furthermore, it also tells something about whether the company has a surplus or deficit.

The information the balance sheet and income statement provide is useful for purposes like profitability and growth analysis. To analyse the reasons behind bankruptcy, the profitability and growth ratios could provide useful information. For instance, one could see signs if a company has had a too big growth in a small amount of time, or indications of so. Therefore, profitability and growth analysis could help to supplement and explain the detailed information from the balance sheet and income statement. Furthermore, such analysis could also help with future profitability and growth to establish future profitability for other startups.

3 LITERATURE REVIEW

From thoroughly searching Google Scholar, Web of Science, and Research Gate for academic articles on why startups go bankrupt, the key findings are that a lot of the research focuses on how startups can succeed rather than why they go bankrupt. There is also a dominance of qualitative research methods on this topic, and very few quantitative.

In 2016, Krishna, Agrawal and Choudhary published an article titled “Predicting the Outcome of Startups: Less Failure, More Success”, and has received several awards for their article. Some of their key points are that "on an average 9 out of 10 startups fail (industry standards)", and "several reasons are responsible for the failure of a startup including bad management, lack of funds, etc." (Krishna, et al., 2016, p. 798). In their article, they have used different sources such as TechCrunch, Crunchbase, etc., and has developed a model that helps startups to prioritise "which factors they need to focus more on, to hit the success mark" (Krishna, et al., 2016, p. 798). One of their wishes is to take their approach and model and evolve it into a web tool for innovators and entrepreneurs.

The article “Startups’ Roads to Failure” was published in July 2018 by Marco Cantamessa and his colleagues, who all work and or is connected to Polytechnic University of Turin (Cantamessa, 2018). Their article analyses the reasons why startups may fail and try to develop a method one could use to recognise these patterns and or reasons that they discover in their article. However, this article is not of the highest quality if one were to use it as a reference. This is due to the authors not being connected to a recognised university within the startup field, low number of citations, and not published in a publication that is highly recognised. But, unknown authors dominate the research field for startups. Moreover, the research within the startup field strongly focuses on how to be successful and not reasons behind the disappearance of the firm.

Torger Reve is a professor at BI Norwegian Business School at the department of strategy and entrepreneurship. Reve is also recognised within the Norwegian startup field. His research field centres around the advantages and contributions that successful startups bring to the business environment in Norway. In August 2017 one of his articles was published in MIT Reap, titled "From Start-ups to Scale-ups". MIT Reap is a Regional Entrepreneurship Acceleration Program (REAP) directed by Massachusetts Institute of Technology (MIT). The purpose of this programme is to assist regions to develop evidence-based and action-oriented strategies for the development of the ecosystem for innovation and entrepreneurship (OsloMet, 2019). The takeaway from Reve's article is how the decision of satisfactory strategy for growth is the largest difficulty for startups, and not necessarily to create a new company.

As previously mentioned, the majority of the research about startups focuses on either qualitative methods and how to succeed. Brüderl et al (1992) wrote an article that was published in the American Sociological Association (ASA), titled "Survival Chances of Newly Founded Business Organizations". The authors point out the following three factors, based on previous research, is found to influence the survival of new companies: " (1) individual characteristics of the founder; (2) attributes, structural characteristics, and strategies of the new business itself; and (3) conditions characterizing the environment of a new firm (Brüderl, et al., 1992, p. 227). Furthermore, the authors point out, based on previous research, that the survival for a startup is also influenced by the entrepreneur itself and his or her characteristics. One theory that captures these characteristics is the human capital theory. However, "for organizational and environmental determinants of survival chances, the organizational ecology approach promises theoretical progress" (Brüderl, et al., 1992, p. 231).

4 METHODOLOGY

Before knowing what data we need, we need to think about which methodology we want to use. We have decided to use a quantitative method, using relevant financial ratios and models to find any explanatory factors in Norwegian startups' bankruptcies. Also, we will use these ratios and models to compare bankrupt startups with successful startups to see if there are any common denominator in the financial statements. This comparison will be made to support the theory of being an explanatory factor for bankruptcy or to see if it is the same for the successful firms as for the bankrupt ones and therefore not an explanatory factor for bankruptcy. However, to support our findings we will use some qualitative research on the topic as well.

We would like to see if there are enough data to focus on one industry or if we are looking at all industries and then split the different ratios and models in the different industries to get the proper results and comparisons due to industry-specific reasons. From the results the ratio analysis gives us, we will make different regression models based upon the interesting findings. There are two different ways we are looking into to write the thesis if we look at all industries, and those are:

- Make separate sections in the thesis industry by industry and make a full analysis for each industry separately, or
- Analyse each ratio first at an overall basis and then at each industry level to capture abnormalities, and get a thorough analysis for each of the ratios before making the regression models.

4.1 BALANCE SHEET ANALYSIS

First, we want to investigate if there are any indications of a potential bankruptcy shown in the balance sheets of the bankrupt startups relative to the successful ones. There are numerous ways to do this, and we are going to analyse different ratios and measures for the balance sheet first. Thereafter, probably make probit and or logit models to see if these findings can relate to bankruptcy or if it could have been predicted. We will also do this for the income statement, profitability and growth analysis.

When we get the data we need, we will look for bankrupt startups with high inventory, if there are any. Having a high inventory is costly, and depending on what kind of inventory it is, some inventory might go bad before it is sold leading to inventory loss. Therefore, we would like to test if high inventories are due to low or no sales for the startups that go bankrupt within four to five years versus those that do not, through inventory turnover. We might look at other factors related to high inventory as well, and look at the evolvement in inventory for the two groups of startups.

Managing receivables is an important part of a business' finances. For that reason, it is natural to look into accounts receivables for the two groups of startups. Of course, a high accounts receivable is good, but only if it will be collected. If the startups have mounting unpaid receivables it can mess up its cash flows, and lead to its liabilities to shadow the business' revenues. We would like to test if there is a significant difference between the bankrupt firms and the successful firms using debtor days. Are the debtor days different due to longer/shorter credit time in general, or are receivables just not collected?

The relationship between debt and financial liabilities against shareholders equity shows the capital structure within a company. The debt to equity ratio is used to show whether a company is funded more by either borrowed capital or equity funding. A high d/e ratio indicates a levered company with mostly debt, thus a low d/e ratio indicates an unlevered company leaning towards more equity funding. If a company has a good cash flow, it could be preferable with a high d/e ratio, but a declining company should not have a high d/e ratio. We are curious to see if the capital structure is similar for those that go bankrupt (possibly high d/e ratio) versus the ones that do not (high or low d/e ratio).

One way to see if a company could be at risk of going bankrupt is to look at its cash & equivalents and short-term investments, versus current liabilities and long-term debt (excluding receivables and other assets). Therefore, it would be interesting to look at the two different groups and see if there are repeating low cash & equivalents and short-term investments, and high total debt for the bankrupt startups with opposite findings for the successful startups. Maybe there is no correlation at all, which makes this exciting to look into.

Looking at the working capital of any business one can tell if it can pay its current liabilities without having to borrow money, sell equipment or maybe having to liquidate inventory. Thus, negative working capital can mean that the business is having an efficient working capital management, where inventory is sold quickly and cash is collected quickly through carefully managing receivables, payables and inventory. This can allow invoices to be paid on the due date such that more inventory can be purchased and in that way not tying up cash. In other words, the working capital itself does not tell much without any context. Therefore, the interesting thing to see will be if there is any common thread for the two different groups of startups or not.

Working capital can be measured by the current ratio, a liquidity ratio, and it equals current assets divided by current liabilities. A current ratio above 1 shows that the company holds more current assets that can be converted into cash than they have in current liabilities, and in general it should preferably be around 1.5. Thus, the current ratio should probably not be higher than 3 since this indicates that the company has inefficient cash management. We are wondering if the startups generate enough cash to pay off its short-term debt on the due date, or not. Also, it will be interesting to see the difference between the two different groups of startups, if any.

Another ratio to look into is the quick ratio and is calculated by dividing the quick assets by current liabilities. The quick assets are the current liabilities less inventory since inventory is the least liquid current asset that cannot be converted into cash before it is sold. This ratio is used to measure a company's liquidity and the ability to meet its current or short-term liabilities with its most liquid assets. The reason we want to look into this goes for the same as for the current ratio, only to see if they can pay off its short-term debt when it is due, without having to sell inventory.

4.2 INCOME STATEMENT, PROFITABILITY AND GROWTH ANALYSIS

The income statement contains a lot of important information about a business' financial information and is therefore important to look into. Also, profitability is key for any business to survive, but growth is essential for its long-term survival. Therefore, it is necessary to look into these categories and see if there is anything to discover. Hopefully, there is a lot to find and compare, and we are curious to see what we find.

Net profit margin shows how profitable a company is, taking all aspects of the income statement into account. This margin shows how much money a business is making at the bottom line as a percentage of total revenues. The only downside with the net profit margin is that it takes one-time costs and gains into account that might make compatibility harder. Two other profitability ratios we can look into is the operating profit margin and the gross profit margin. The operating profit margin shows the earnings/operating profit as a percentage of sales before deducting income taxes and interest expenses. Businesses that have a high operating profit margin often have a better ability to pay their fixed costs, and in an economic slowdown, they often have a higher likelihood of surviving. The gross profit margin, on the other hand, shows how much money a business is making after only subtracting the cost of making the product from the total income revenue. If a company has a low gross profit margin, there is a high probability that the company is going to struggle with covering operating expenses, dividends, depreciation and fixed costs. All of these three ratios are relevant for this thesis, but we will have to see from the data we collect if we are using one, two or all of them.

Return on assets (ROA) is shown as a percentage of a company’s net income divided by its total assets. This ratio displays how well a company generates earnings by how they are using their assets. A high ROA means that the company is good at utilizing its assets to generate income. We are intrigued to see whether the bankrupt startups somewhere along the way were close to the overall industry preferred return on assets of 5%, or if it was volatile from the start till the end.

Return on equity (ROE) displays the percentage of a company's net income divided by its stockholders' equity and shows the rate of return on the money invested by the equity holders. Investors and stock analysts usually look at the ROE ratio before purchasing a company's stock. The reason behind this is because a high ROE can imply that the company can generate cash internally, and thus not too reliant on debt financing. From the bankrupt startups, would investors or stock analysts want to invest in them a year or two before going bankrupt? Or did they ever have a somewhat satisfactory return on equity?

As previously mentioned, growth is essential for any business' long term survival, and therefore we would like to look at the sustainable growth rate for the startups. One way to find the sustainable growth rate for a company is to take the earnings retention rate for a company and multiply it with its return on equity. The earnings retention rate shows the rate of how much the company has in retained earnings relative to its net income. This ratio can be interesting to look at for startups since one could think that startups do not pay any dividends in their first years in business.

It will be interesting to see how many of the startups that have a lower sustainable growth rate than its return on equity and if this has an impact on bankruptcy since in general a high growth rate is considered riskier than a low growth rate.

4.3 DATA SPECIFICATION

To get good analysis' that can be reliant we need all the financial information there is for as many startups as possible, in the given period from 2000 to most recent, that has gone bankrupt within four to five years in business. Furthermore, we need the same information for the same amount of companies for successful startups within the same period.

5 DATA

Depending on the different ratios and measures we use, we will create a tailored regression model with relevant variables for calculating the likelihood of going bankrupt given a specified difference in certain ratios. We wish to use a probit or logit regression for calculating the probability of bankruptcy. Once our methodology is set, we will apply for access to the Centre for Corporate Governance Research (CCGR) database and once our application on what information we want to retrieve is approved, we will retrieve the necessary information. Therefore, our information is based on secondary data.

> *The Centre for Corporate Governance Research (CCGR) focuses on empirical research and primarily studies Norwegian firms. The projects often use data that are difficult to obtain in other countries (such as unusually detailed ownership data for listed firms and high-quality accounting data for non-listed firms) or that reflect institutional environments which are unique internationally (such as mandatory representation of employees and females on the board of directors). The CCGR pays special attention to the private industry in general and to non-listed firms and family firms in particular (Østergaard, 2020).*

We want to have a time constraint on our data, but to what extent is difficult to determine before we can see the available information from the CCGR database. We hope to limit it to companies who have existed four to five years, before going bankrupt. Moreover, we want to look at companies in the timespan of 2000 to as recent as possible. Furthermore, we want to focus on companies within Norway, from a general point of view. We will also conduct comparisons between the successful and unsuccessful ones, to get a better understanding of the abnormalities. Furthermore, we will test if our model holds by checking if it also applies to the industry level. What industry we choose to look at will be based on what data from the CCGR database within the different markets which has shown the best data quality.

Whether we need additional data to support what we find in the CCGR database is uncertain, since the access to this database is only granted after one has decided what information one want to collect. We have not yet decided if we are going to adjust for risk for the relevant market we want to examine and if we are going to then how we will collect data to conduct an adjustment.

Our main difficulty in regards to data is whether the CCGR database will provide us with satisfactory information. If we do not find the data that we need, we will run into a problem and would have to find additional data ourselves. But, our supervisor has assured us that this will probably not be a problem. Since we at this point do not have access to the CCGR database, we are not able to make a summary of the collected data.

6 PROGRESSION PLAN

In this section, a tentative progression plan/goal is made for the 4th semester of our master programme. To try to secure continuous progress in our work, we have set up specific milestones. This results in a slightly detailed progression plan. Furthermore, one overall goal would be to finish the master thesis by June 1st to have some time to rewrite and or polish our work. Throughout the semester, we will be in contact with our supervisor Ignacio for any arising questions and ask for help through the use of email and or meetings. As well, in regards to time spent to master thesis supervision by our supervisor will be aligned with the guidelines provided by BI.

January: Finish the preliminary master thesis report, and ask our supervisor if there are any arising questions after submitting the report. Moreover, we need to start to decide how our model will look to collect data from the CCGR database and apply for access to this database.

February: Work on implementing our data into our model, and clean the data. Also, collect more relevant sources with different viewpoints for use in the literature review.

March: Work on the programming part with our data and model, and set up all the necessary details. Will also try to collect any missing information.

April: Continue the work from March, and also try to find sources that could support and or question our findings. Furthermore, we will try to finish up the model so it can be used satisfactorily.

May: Collect and analyse the results. Use the results to write the thesis.

June: Polish our work, and do the necessary rewriting. Submit the final thesis by the end of June.

7 REFERENCES

Feinleib, D. 2011. Why Start Ups Fail: And How Yours Can Succeed. Apress; 1st ed. Edition (March 28, 2012).

Brüderl, J., Preisendörfer, P., and Ziegler, R.. (1992). Survival chances of newly founded business organizations. American Sociological Review, pages 227–242.

Cambridge Dictionary. (2020). *Start-up*. Retrieved from https://dictionary.cambridge.org/dictionary/english/start-up

Cantamessa, M. et. al. (2018). Startups' Roads to Failure. *Sustainability*, MDPI. DOI: 10.3390/su10072346

Corporate Finance Institute Education Inc. (2020). *Debt Equity Ratio; How much leverage does a company have?*. Retrieved from https://corporatefinanceinstitute.com/resources/knowledge/finance/debt-to-equity-ratio-formula/

Corporate Finance Institute Education Inc. (2020). *Profitability Ratios*. Retrieved from https://corporatefinanceinstitute.com/resources/knowledge/finance/profitability-ratios/

Corporate Finance Institute Education Inc. (2020). *Sustainable Growth Rate; Evaluating how quickly a business is growing year-over-year*. Retrieved from https://corporatefinanceinstitute.com/resources/knowledge/finance/sustainable-growth-rate/

Holm, E. D. (2018). *62 000 nye bedrifter så dagens lys i 2017*. Retrieved from https://www.dnbnyheter.no/bedrift/62-000-nye-bedrifter-sa-dagens-lys-i-2017/

Hvamstad, E. (2017). *Tre av fire konkurs etter fem år*. Retrieved from https://finansavisen.no/nyheter/naeringsliv/2017/03/tre-av-fire-konkurs-etter-fem-aar

Kennon, J. (2019). *Analyzing a Sample Balance Sheet From Microsoft*. Retrieved from https://www.thebalance.com/analyzing-a-sample-balance-sheet-microsoft-357265

Kennon, J. (2019). *How To Analyze A Balance Sheet*. Retrieved from https://www.thebalance.com/investing-lesson-3-analyzing-a-balance-sheet-357264

Kennon, J. (2019). *The Basics of Income Statement Analysis*. Retrieved from https://www.thebalance.com/investing-lesson-4-income-statement-analysis-357580

Krishna, A., Agrawal, A. and Choudhary, A.. (2016). Predicting the Outcome of Startups: Less Failure, More Success. *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*, Barcelona, 2016, pp. 798-805. DOI: 10.1109/ICDMW.2016.0118

Najjar, D. (2019). *Red Flags In Your Financial Statements*. Retrieved from https://www.thebalancesmb.com/red-flags-in-your-financial-statements-3958554

New Century Financial. (2020). *Managing Receivables to Ensure a Healthy Cash Flow*. Retrieved from https://www.newcenturyfinancial.com/managing-receivables-to-ensure-a-healthy-cash-flow/

OsloMet. (2019). *MIT Reap*. Retrieved from https://ansatt.oslomet.no/mit-reap

Visma. (2020). *Balanse*. Retrieved from https://www.visma.no/eaccounting/regnskapsordbok/b/balanse/

Visma. (2020). *Resultatregnskap*. Retrieved from https://www.visma.no/eaccounting/regnskapsordbok/r/resultatregnskap/

Wall Street Prep, Inc. (2020). *Working Capital: Formulas, Misconceptions and Real Examples*. Retrieved from https://www.wallstreetprep.com/knowledge/working-capital-101/

Reve, T. (2017) *«Arbeidsplassene skapes i de nye vekstbedriftene»*. Retrieved From https://www.bi.no/globalassets/forskning/forskningskommunikasjon/rapporter/mit-reap-sluttrapport-2017.pdf

Reve, T. (2018). *How to scale new companies*. Retrieved from https://www.bi.edu/research/business-review/articles/2018/11/how-to-scale-new-companies/

Østergaard, C. (2020). *Centre for Corporate Governance Research*. Retrieved from https://www.bi.edu/research/find-departments-and-research-centres/research-centres/centre-for-corporate-governance-research/