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The financial health of Norwegian crowdlending borrowers

Comparing crowdlending borrowers and borrowers in traditional banks by applying three bankruptcy prediction models

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Master's thesis, Economics and Business Administration, Finance

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

The purpose of this thesis is to examine whether companies obtaining loans at Norwegian crowdlending platforms are more likely to default than companies obtaining loans in traditional Norwegian banks. Crowdlending, the concept of lending directly from large groups of investors through a digital platform, has experienced an explosive growth in Norway and worldwide over the last years. Despite this, research regarding this topic is limited. To the best of our knowledge, this is the first study to examine the financial health of Norwegian crowd borrowers.

In our empirical study, we use three proven models for prediction of bankruptcy and analyze whether Norwegian crowd borrowers' credit quality is different than that of regular Norwegian borrowers. The analysis is conducted on a dataset constructed from manual collection of Norwegian crowd borrower information from the three Norwegian crowdlending platforms Monner, FundingPartner and Kameo. To create an approximately randomized experiment with suitable comparable traditional borrowers we applied the matching approach of Coarsened Exact Matching.

Based on our analysis, there is not enough evidence to suggest that Norwegian crowdlending borrowers are riskier than borrowers in traditional banks. Although the mean and median credit scores of crowd borrowers are generally worse than those of the regular borrowers, thus suggesting a difference in credit quality between the groups, these differences prove to be statistically insignificant.

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The choice of topic was based on our common interest in financial technology (FinTech) and new financial trends. Our interests resulted in a thesis on the topic of lending-based crowdfunding (crowdlending). We found the work to be challenging, but rewarding, and we are left with knowledge and competence on a specific topic on which little research has been done.

Finally, we would like to express our gratitude to our supervisor Carsten Bienz for his constructive and accurate feedback. His guidance and support throughout the writing process improved the quality of our thesis.

Norwegian School of Economics

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Section 1 – Introduction

For centuries, owners of small and medium sized businesses have been dependent on the grace of banks to realize their dreams. The rejection of loan applications based on strict and often predefined criteria have restricted many businesses' access to much-needed capital. Crowdlending, the idea of lending directly from large groups of private investors, has gained a lot of positive attention in the last years. With crowdlending platforms, businesses who fail to get a loan elsewhere can meet their financing needs.

The purpose of this thesis is to examine whether companies obtaining loans at Norwegian crowdlending platforms are riskier than companies obtaining loans in traditional Norwegian banks. Crowdlending, the concept of lending directly from large groups of investors through a digital platform, has experienced an explosive growth in Norway and worldwide over the last years. Despite this, research regarding this topic is limited. To the best of our knowledge, this is the first study to examine the financial health of Norwegian crowd borrowers.

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Based on our analysis, there is not enough evidence to suggest that Norwegian crowdlending borrowers are riskier than borrowers in traditional banks. Although the mean and median credit scores of crowd borrowers are generally worse than those of the regular borrowers, thus suggesting a difference in credit quality between the groups, these differences prove to be statistically insignificant.

Crowdlending is a reward-based form of crowdfunding, where individuals can invest their money by providing loans to businesses and individuals and get interest payments in return. This paper focuses on business lending, where a group of individual investors provide a loan to a business borrower (Ziegler et al., 2020). The platforms themselves do not lend out any money but serves as a certifying agent, so that investors can lend through the platform to companies looking to raise capital. Crowdlending has experienced an explosive growth worldwide, and the business lending segment alone generated \$50.3 billion in market volume in 2018 (Ziegler et al., 2020). Crowdlending accounted for 16,5% of the total alternative finance industry transaction volume in 2018, a market that grew by 48% excluding China (Ziegler et al., 2020).

In Norway, crowdlending is still a nascent industry, but we have already seen several platforms established within the last decade. Crowdlending has the largest market share of crowdfunding activities in Norway, boasting a total lending volume of approximately 100 million NOK in the period between 2018 Q1 and 2019 Q1 (Norges Bank, 2019). Although the market is rapidly growing, Norwegian platforms have so far been unable to make profits, and the number of accepted borrowers is very limited. The Norwegian government has imposed several regulations on the crowdlending market, most notably requiring platforms to obtain concessions as banks to be allowed to operate.

Crowdlending platforms serve a dual role: As a facilitator for businesses looking to raise capital, and as an interesting investment opportunity for investors. The platforms' risk assessments are of great importance to both parties - SME's hope to be met with a less rigid judgment than that of banks, and investors want the platforms to minimize their risk while maximizing their returns. We therefore find a study of crowd borrowers' credit quality to be particularly interesting, as it will indicate whether the platforms are taking on higher-risk loan takers than banks. Have crowdlending platforms found a goldmine under the nose of underserving traditional banks, or are they just another overhyped financial trend?

Research on the credit quality of crowd borrowers is very limited. The emphasis in crowdlending research has so far been on qualitative studies on crowdlending success criteria, including Moreno-Moreno et al. (2018) and Shneor & Aas (2016), or market reports like Ziegler et al (2020). Gjesvik and Hestmann (2018) studied whether crowdlending borrowers at two French platforms performed worse than regular borrowers in four credit scoring models. As for the Norwegian market, the infancy of the market and strict regulatory measures may have limited research up until this point.

The short life span of crowdlending in Norway also means that very little data exists. Therefore, we have manually constructed a dataset of Norwegian crowd borrowers. Crowd borrowers were identified at the three Norwegian crowdlending platforms Monner, FundingPartner, and Kameo, and financial data was downloaded from the business database Proff.no. In total, 125 Norwegian crowd borrowers were identified. We also created a control group of more than 57 000 companies by downloading data from Proff.no.

To create an approximately randomized sample of regular borrowers for comparison, we have applied the matching technique of Coarsened Exact Matching to our dataset. The matching process is important as heterogeneity between companies in the borrower groups could potentially lead to our results being biased and not representative of the actual population. The Coarsened Exact Matching procedure reduced bias in the dataset, as well as the data's imbalance score. Borrowers were matched on age, geography, industry, and key financial variables from 2017. We also winsorized our data to remove the influence of potential outliers and increase robustness of our results. Our analysis is performed on both the winsorized and unwinsorized datasets for comparison.

In our analysis, we apply three well-sited bankruptcy prediction models to our dataset of crowd borrowers and regular borrowers. The models assign each company with a credit score indicating probability of failure within a given time frame. Based on the score results, we perform a t-test on the groups' mean scores to check for differences between crowd borrowers and regular borrowers. Regardless of which bankruptcy prediction model that is applied, the results give no evidence to suggest differences in mean credit scores between regular borrowers and crowd borrowers. We also perform Wilcoxon's rank sum test to test for difference in the groups' median score, which also yields no evidence to suggest a difference. We find that a higher share of crowd borrowers is classified as financially distressed based on the three credit models' cut-off zones, but the differences are not statistically significant. In other words, our analysis yields no evidence to suggest that crowd borrowers on average have a higher probability of defaulting their loans compared to regular borrowers.

We also test to see if there are differences between the credit quality of the different platforms' clients to see if any platforms take on higher-risk borrowers than the others. The platforms all conduct thorough credit assessments and other qualitative assessments when reviewing loan applications, and our results do not indicate a difference between the platforms' level of risk. This is important as the platforms are relying on having a large investor group who trust their risk assessments in order to make revenue.

Our findings indicate that Norwegian banks might be underserving the credit market by refusing loans to companies who are financially suited to service them. If true, it has a negative effect on the real economy, as underserved credit markets lead to reduced aggregate investment (Buca and Vermeulen, 2017; García-Posada, 2018). We hope to shed some light on this issue with the findings in this paper.

The structure of the thesis is as follows. Section 2 provides a review on the literature that form the theoretical basis of our thesis. Section 3 presents our method of matching and bankruptcy prediction models in detail, and section 4 presents key statistics on our data, as well as our data collection and preprocessing methods. In section 5, the results of our analysis are presented, including descriptive statistics on our credit scoring results and t-tests to determine if there are significant differences in credit scores between crowd borrowers and regular borrowers. Section 6 contains in-depth discussions on our results and the implications of them, and section 7 presents possible limitations of our thesis. Finally, we present the conclusion of our thesis in section 8.

Section 2 – Background

This section will provide an insight into the basics of crowdlending, the global and Norwegian crowdlending markets, and how crowdlending can affect the original banking system.

2.1 Introduction to crowdlending

Crowdlending is a form of crowdfunding, which can be defined as "the setting in which a large audience raises an amount of money, where each individual in the audience contribute with a relatively small amount" (Belleflamme et al., 2014). Crowdlending falls under the subcategory of crowdfunding called reward-based crowdfunding, where the contributor gets something tangible in return for their money (FundingPartner, 2017). In the case of crowdlending, the tangible returns are interest payments.

The interaction between people who are willing to contribute with capital, and those who are raising capital takes place on online platforms, known as crowdlending platforms (Belleflamme et al., 2014). These platforms serve as certifying agents so that investors can lend through the platform to companies looking to raise capital. The platforms provide information of the company, like product or project, market, key financial information, board members and future plans. This information makes it easier for investors to make informed decisions on which company to invest in.

Ziegler et al. (2020) separate between two types of peer-to-peer lending: Consumer lending, where individuals provide loans to consumer borrowers, and business lending, where individuals provide loans to business borrowers. These loans can be unsecured or secured through property or other securities. This paper will focus on business lending, using data from three Norwegian peer-to-peer business lending platforms.

2.1.1 Global market

Ziegler et al. (2020)'s report "The Global Alternative Finance Market Benchmarking Report" states that peer-to-peer Business Lending generated $50.3 billion in market volume in 2018, accounting for 16.5% of the total alternative finance industry transaction volume. China is the largest market for peer-to-peer lending but experienced a sharp decline in transaction volume in 2018, falling 39.8%. However, the global alternative finance market excluding China grew by 48%. In Europe, the UK market is by far the largest, accounting for as much as 72% of the European P2P Business lending transaction volume in 2018 (Ziegler et al., 2020).

2.2 Crowdlending in Norway

The Norwegian crowdlending market is growing but still relatively small. In 2019, Norges Bank conducted a survey about crowdfunding in Norway. The participants of the survey were individuals and platforms engaged in equity-based crowdfunding and lending-based crowdfunding (crowdlending). Norges Bank's (2019) findings suggest that crowdlending had the largest market share of crowdfunding activities with a total lending of approximately 100 million NOK in the period between 2018 Q1 and 2019 Q1. Out of these 100 million NOK, lending to real estate projects represented the largest share and consumer credit represented approximately 5%.

This paper uses data from three crowdlending platforms that operate in Norway: Monner, FundingPartner, and Kameo. FundingPartner and Monner only operate in the Norwegian market, while Kameo operates in Norway, Sweden, and Denmark. *Table 2.1* contains summarized key information about the platforms.

Table 2.1: *Summarized information regarding Norwegian crowdlending platforms*

Platform	Monner	FundingPartner	Kameo
Markets	Norway	Norway	Norway, Sweden and Denmark
No. of Norwegian clients (02.2020)	54	45	26
Service fee	2.5%	2.5% - 3.5%	2% - 5%
Established	2014	2016	2014
2018 result	- 15 047' NOK	- 2445' NOK	- 3508' NOK

As *table 2.1* shows, the platforms are established within the last 6 years, and none of them are yet profitable, presenting sizeable net deficits for 2018. In other words, the Norwegian market seems to be unsettled and not yet profitable for its platforms.

2.2.1 Role as a disruptor in the Norwegian credit market

In recent years there has been a rising tendency to use alternative digital financing platforms in many countries. Traditional banks offer new digital services and banking solutions, and new digital participants establish equity and credit platforms based on financial technology (Norges Bank, 2018). Norges Bank (2017) states that alternative financing platforms, such as crowdlending, can help the original banking system to reduce credit and concentration risk by spreading lending across a larger number of market participants outside the banking system. In Norway, the number of new market participants continues to increase within lending-based crowdfunding.

Norges Bank (2019) states that crowdfunding and issuance of credit on digital platforms are examples of how new actors can impact the competition in the credit market. So far, this modern way of extending credit is very limited and the profitability of the banks are unaffected in Norway. Crowdlending makes credit more accessible for individuals and businesses that have problems to obtain credit or loans in banks. This could in turn lead to an increase in overall debt in the economy, and thereby increase the credit risk outside the banking system (Norges Bank, 2017).

Our analysis is built on the assumption that traditional banks and crowdlending platforms compete for the same customers. Further, we assume banks to be the first choice for businesses looking to raise capital. These assumptions are based on our observations of the interest rates that are offered through banks and crowdlending platforms. According to SSB the average interest rate in business lending to non-financial firms was ranging from 3.53% to 4.03% throughout 2019 (SSB, 2020). Our data from Norwegian platforms shows an average interest rate of 9.7% for investors, with an additional 2-5% service fee added by the platforms. Although the platforms showcase interest rates as low as 5% (FundingPartner (2020); Kameo (2020); Monner (2020)), our data shows that the interest rates of 89% of all loans distributed as of February 2020 were 9% or higher, not including service fee. In other words, companies raising capital through crowdlending can expect to pay a substantially higher premium than banks' loan takers. Banks are therefore still likely to be companies' first choice when raising capital.

2.2.2 Regulations on crowdlending in Norway

Finans Norge points out that Crowdfunding will be a valuable source for the Norwegian start-up industry in the future. For this to happen there must be established an expedient regulation in addition to the established regulatory framework (Bellamy & Opland, 2017). Several regulatory measures have already been taken on the Norwegian crowdlending market. Businesses that manage financing through lending platforms need a concession as a bank or financial institution, and if the business owning the platform receives deposits from the public, they need a concession as a bank (Karlsen & Steffensen, 2017).

Crowdlending platforms are essentially loan intermediaries, which is an independent intermediary with the task of mediating contact between borrowers and lenders and helping them negotiate loan agreements (Karlsen & Steffensen, 2017). The law strictly forbids loan intermediaries to by itself lend funds or assume any risk of losses in the loans being brokered (Karlsen & Steffensen, 2017). This means that crowdlending platforms are not allowed to have any interest or own funds in the loans being issued. If a crowdlending platform undertakes a settlement function upon paying out and repaying loans, a license is required as a payment company. Thus, a crowdlending platform as a payment institution can only receive money to be used to carry out a payment service. To obtain deposits on their platform they need to obtain a bank license.

Another important regulation is the ban on auto-investing. According to Bore (2019), crowdlending platforms are not allowed to spread lender risk by spreading investments on different loans at the platform. This kind of diversification would probably lead to a reduction in total risk of the investors. Outside Norway, auto-invest functions are frequently used.

2.3 Crowdlending platforms' assessment of financial health of crowd borrowers

The three Norwegian crowdlending platforms all perform a thorough credit assessment before accepting loan takers. Loan applications are required to provide extensive financial and non-financial data, which will also be made available to possible investors if the application is accepted. Moreno-Moreno et al. (2018) claim that most lenders tend to analyze their investment options based on traditional financial credit scores, and that they prefer to lend money to the highest rated companies. Credit scoring could therefore be considered a vital part of the platforms' role to reduce informational asymmetry and give their investors sufficient information.

The methodology varies between the platforms. FundingPartner (2019) states that their credit assessments are based on debt servicing capacity, financial management and general management of the company, amongst other things. Monner uses the credit reporting agency Experian to perform credit scoring of their loan applicants, as well as doing a background check of the applicants' management (Monner, n.d.). Kameo also gets external credit reports on their applicants, as well as using a credit scoring model developed in-house (Kameo, n.d.). According to Kameo's own material, the internal model will very rarely rate a company higher than the external reports do.

Gjesvik & Hestmann (2018) examine whether there is a significant difference in credit quality between crowd borrowers and regular loan takers, by applying credit scoring models on crowd borrowers from the French crowdlending platforms Lendix and Credit.fr. They find that three of the four models give lower credit scores to companies borrowing through crowdlending platforms compared to regular borrowers and conclude that crowdlending borrowers have lower credit quality than regular borrowers.

Section 3 – Method

In this section we will give an in-depth description of the approach we have used to compare the financial health of crowd borrowers versus regular borrowers. We will describe the matching method that we have applied and explain the relevant variables that we have selected and used in the matching procedure. We will also present the bankruptcy prediction models used to calculate credit scores and give a brief explanation of the econometric techniques used in the analysis.

3.1 The econometric matching approach

In order to compare companies that have obtained loans at Norwegian crowdlending platforms (defined as crowd borrowers) to Norwegian companies that have obtained loans in traditional banks (defined as regular borrowers), we should select a group of regular borrowers who are as similar as possible to the group of crowd borrowers. The reason is that observed or hidden heterogeneity between participants in the two groups of borrowers can lead to potential bias in the results. We therefore need to implement a reliable procedure of econometric matching, which is a statistical technique that evaluates the effect of a specific incident, action, or treatment by comparing two groups of observations.

3.2 Matching

Iacus, King & Porro (2012) state that matching is a statistical technique that evaluates the effect of a specific incident, action, or treatment by comparing two groups of observations. The main purpose of matching is to recreate properties of experimental data (randomization) by establishing a control group that is similar to the treatment group. In our case, the purpose is for every crowd borrower to be matched with at least one regular borrower with similar key characteristics. This yields a better balance of characteristics between the group of treatment units and control units, and an empirical distribution of the covariates that is more equal (Blackwell, Iacus, King & Porro, 2009). A parametric model for controlling covariates such as linear regression could be used if the data is approximately balanced (Blackwell et al., 2009). Holmås & Kjerstad (2010) point out that unobserved heterogeneity between participants and non-participants can lead to potential bias in the results, but a good procedure of matching can make heterogeneity less important. If there is an uneven number of regular borrowers being matched with the number of crowd borrowers, a weighting of observations is required for further analysis (Blackwell et al., 2009).

3.2.1 Matching methods

Several matching methods are discussed in the literature. Some popular methods are Exact Matching (EM), Propensity Score Model (PSM), and Coarsened Exact Matching (CEM*)*.

Exact Matching matches observations in the treatment group to observations in the control group with the exact same characteristics (Blackwell et al., 2009). As the name implies, this matching procedure requires treatment units and control units to be exactly matched on all variables, thus typically returning few matches. If the dataset consists of continuous variables, exact matching is unlikely to happen, because of the low probability of having the exact same value on a continuous scale. One way to overcome this problem is to divide continuous variables into different intervals using Coarsened Exact Matching (Iacus et al., 2012).

Coarsened Exact Matching is a matching method designed to improve estimation of causal effect, and according to Blackwell et al. (2009), the method has obtained significant support in the literature in recent years. A powerful characteristic of CEM is the possibility of choosing the coarsening manually rather than using automatic computer-based algorithms. This method is such that it is possible to have exact matching on some variables and use broader intervals on others. This allows the user to set the maximum level of imbalance upfront. Iacus et al. (2012) argue that CEM is dominant in its ability to reduce imbalance, bias, estimation error, variance, mean squared error and model dependence. Other favourable properties of the method include speed of estimation, simplicity, requiring fewer assumptions and being easy to automate (Blackwell et al., 2009).

Propensity score is a matching method that finds comparable observations in a dataset based on an index value. Instead of matching on single variables the idea is to collect all variables into a number, called an index. The closer the index value is for the observations, the more comparable two observations are. An advantage of this method is that it can be used with many different attributes, but it does not work well with for example industries or years (Bienz, 2017). King & Nielsen (2019) also argue that Propensity Score Matching often achieves the opposite of its purpose, thus increasing model dependence, imbalance, inefficiency, and bias.

3.3 Coarsened Exact Matching

We chose to use Coarsened Exact Matching (CEM) because Propensity Score Matching often yields increased model dependence, imbalance, inefficiency, and bias (King & Nielsen, 2019), and that CEM is a more flexible method than Exact Matching (EM). CEM allows the user to choose between exact and coarsened matching on each selected variable, and causal estimates based on the CEM pre-processing procedure possesses many powerful statistical properties, as mentioned in section 3.2.1.

3.3.1 The procedure of Coarsened Exact Matching

CEM gives the analyst the opportunity to coarsen their data into meaningful intervals and categories and perform an exact or not exact matching on the coarsened data. The procedure allows us to split continuous variables into categories of the same length, and categorical variables can be given coarser subdivision if needed. When the data is coarsened, a matching between the crowd borrowers and a large set of businesses in the group of regular borrowers is performed. After matching, data from the matched observations is passed on for further analysis. The procedure of Coarsened Exact Matching consists of three steps as stated by Iacus et al. (2012):

Step one - the researcher decides which variables to match on, which variables should be exactly matched and which should be coarsened, and divides the variables into intervals or categories according to a pre-defined criteria or value. An example could be that companies are split into broader or more narrow industries, and that the asset size is split into intervals rather than a continuous scale. *Step two* – the researcher applies the matching in a statistical program which sorts the observations into strata. Each stratum represents a unique combination of the coarsened variables. *Step three* – the researcher aims to discard strata that only contains control units and we retain strata that contain both treated and control units.

3.3.2 Choice of matching variables and bin sizes

The variables and their corresponding bin sizes decide which companies are matched against each other. The choice of variables and bin sizes are therefore important in our analysis. In the literature, there is no definitive answer on what the best approach to choosing variables is.

However, Iacus et al. (2012) state that variables should be relevant, and intervals and categories should be small enough to conclude that companies can be said to be relatively similar, but big enough so that companies end up with matching companies. Based on Hetland, Mjøs & Zhang (2017), characteristics like creditworthiness, size, localization, industry, and age are relevant for how companies demand credit, and how they are met in the credit market. For our purpose of matching we choose the following variables and respective bin sizes:

Localization (regions) – exact match

As of 2020, Norway consists of 11 counties with a large geographical extent. Hetland et al. (2017) state that there are large regional differences in market concentration, number of banks, access to finance, average loan size, and number of companies with loan in percentage of total companies in each region. We want to control for some of the regional differences between the groups of borrowers. Based on Hetland et al. (2017) a division into Norwegian regions would better match the regional breakdown of financing. Therefore, we choose to coarsen the 11 counties into the 5 Norwegian regions, plus Svalbard, represented in *table 3.1*.

Table 3.1*: Coarsening of the location variable from counties into regions*

Region	**Counties**
Østlandet	Innlandet, Oslo, Vestfold og Telemark, Viken
Sørlandet	Agder
Vestlandet	Møre- og Romsdal, Rogaland, Vestland
Trøndelag	Trøndelag
Nord-Norge	Nordland, Troms og Finnmark
Svalbard	Svalbard

Industry classification (NACE-code) – exact match

In Norway, the NACE code system is used for industrial classification according to businesses' activities. The standard is widely used in the European Union and makes it possible to compare and analyze statistical information of companies (SSB, 2009). Examples of codes can be 46.720 and 62.020 that represent "wholesale of fuel and propellant" and "consultancy in relation to information technology". Different industries have different sources of financing and capital structures. Therefore, we performed an exact matching on the five-digit industry classification code.

Age – coarsened

According to SSB (2019), 29.8% of all newly established enterprises were still active after 5 years from their establishment in 2012. The data shows that survival rates of nascent companies have varied with the year of establishment. 50.5% of enterprises established in 2012 survived their first year and 44.5% of enterprises established in 2016 survived their first year.

Hague (n.d.) segments small businesses into 4 different life-stages. The first stage is *birth,* the second is *youth* ranging from 1-10 years, stage three is *maturity* ranging from 11-20 years, and the fourth stage is called *old stage*, ranging from 20 years and older. Based on SSB's statistics on survival and Hague's business lifecycle, we have divided the age variable into four bins: 1-5 years, 6-10, years, 11-20 years, and older than 20 years.

Table 3.2*: Bins for the coarsening of the age variable*

Group	Age
1	3-5 years
2	6-10 years
3	11-20 years
4	> 20 years

Company legal form – exact match

SSB (2019) showed that survival rates of firms where highly dependent on organizational form. They found that 48.1% of AS companies were still in operation after 5 years, whereas for NUF (Norwegian Registered Foreign Company) the number was as low as 8%. We have therefore performed an exact matching on company legal form. Norway has 43 different legal organizational forms (Brønnøysundregistrene, 2019). Out of these forms *Sole Proprietorship, General Partnership, Limited Liability Company and Norwegian Registered Foreign Company* are the most common company forms. Different forms have different properties considering number of owners, capital requirements, responsibilities, tax requirements, social rights, and legal demands. The mentioned properties could potentially affect a company's access to capital.

Total assets (2017) – coarsened

The European Commission (2003) defines an enterprise as *micro* if the balance sheet total is less than or equal to €2m, as *small* if less than or equal to €10m, as *medium-sized* if less than or equal to €43m, and as *large* if balance sheet total is larger than €43m. Our data is given in Norwegian Kroner, and therefore we will use the average exchange rate for 2017, 9.33 NOK/EUR, to convert the bin limits (European Central Bank, 2017). The bins are presented in *table 3.3* below.

Table 3.3*: Bins for the coarsening of assets*

Size	Total assets (NOK 2017)
Negative	< 0,-
Micro	0,- to 19 000 000,-
Small	19 000 001,- to 93 000 000,-
Medium	93 000 001,- to 400 000 000,-
Large	> 400 000 000,-

Total liabilities (2017) – coarsened

The average liabilities of the crowd borrowers are 9.92 MNOK. Based on the distribution of liabilities we have chosen the coarsening presented in *table 3.4* below.

Table 3.4*: Bins for the coarsening of liabilities*

Bins	Total liabilities (NOK 2017)
1	< 0,-
2	0,- to 999 999,-
3	1 000 000,- to 4 999 999,-
4	5 000 000,- to 9 999 999,-
5	10 000 000,- to 49 999 999,-
6	≥ 50 000 000,-

3.3.3 Measurement of imbalance

We want to measure the balance of the data because it gives an indication of how similar the characteristics of our observations are. Balancing the data must be weighed against the loss of information that occurs when borrowers are dropped, meaning it is often suboptimal to fully balance the sample. CEM uses $\mathcal{L}_1$ as a measure of imbalance in independent variables between the crowd borrowers and regular borrowers (Iacus et al., 2012). $\mathcal{L}_1$ is said to work for imbalance as R^2 works for model fit (Blackwell et al., 2009). The formula is as follows:

$$\mathcal{L}_1(f,g) = \frac{1}{2} \sum_{l_1 \dots\dots l_k} f_{l_1 \dots l_k} - g_{l_1 \dots\dots l_k}$$

The statistical element obtains a value in the interval 0 to 1. A perfectly balanced matching solution is indicated by $\mathcal{L}_1 = 0$, and $\mathcal{L}_1 = 1$ represents highly unbalanced data. If the matching procedure is performed efficiently, we would expect a reduction in the value of $\mathcal{L}_1$. If an increase occurs it is an indication of increased imbalance between the groups (Blackwell et al., 2009). The imbalance measures can be found in *table 9.8* in the appendix.

3.3.4 Restricting the matching solution to a k-to-k

Our dataset contains way more regular borrowers than crowd borrowers, and the CEM procedure uses maximal information by default (Blackwell et al., 2009). This could lead to a high difference in the number of regular borrowers and crowd borrowers after matching. A way of overcoming this problem is to use weighting in the further analysis, for instance a weighted difference in means. Another approach, with enough data, is to perform a k-to-k matching to obtain the same number of crowd borrowers and regular borrowers after matching (Blackwell et al., 2009). K-to-k matching yields the best possible match between each crowd borrower and a corresponding regular borrower, and we are not required to use weights in further analyses. At the same time, well-matched data might be deleted when using k-to-k matching, which can potentially increase the variance of our data. We chose to use k-to-k matching as it gave the best imbalance score, and allowed us to perform the analysis without weighting results.

3.4 Models for prediction of bankruptcy

Bankruptcy prediction models are important to several players in the finance industry. The banking industry is interested in maximizing the profit and on its way minimize the amount of defaulted loans (Altman, Iwanicz-Drozdowska, Laitinen & Suvas, 2014), and investors want to calculate the risk of a firm going bankrupt so they can calculate the risk-return ratio. In the literature, there are several different ways of predicting financial distress, probability of default and bankruptcy of businesses. In this thesis we will use accounting-based bankruptcy prediction models. These models use financial information to calculate credit scores that describe the risk of failure of a business. This means that a firm's financial health is predicted based on past performances. These failure prediction models aim to classify firms into a non-failing and failing group with a certain degree of accuracy. By setting an optimal cut-off point where the probability of misclassification is minimized, the firm will be classified as non-failing or failing according to their individual score obtained (Balcaen & Ooghe, 2006).

To assess the financial health of the crowd borrowers and regular borrowers we will calculate their credit scores based on our three chosen bankruptcy prediction models. Our choice of bankruptcy prediction models has mainly been influenced by two factors: Their performance in the literature, and whether the variables needed are available in our data. We have chosen to use three prediction models so we can check whether the results we obtain are valid across multiple bankruptcy prediction models. Our three chosen bankruptcy prediction models meet our criteria of having a high prediction accuracy and being applicable on our data. Each model has its own credit score zones which are separated by model-specific cut-off values. These zones represent the interpretation of the financial health of the borrowers. The chosen bankruptcy prediction models are presented in the following sections, and a summary of the mathematical model formulations, financial ratios, description of ratios and cut-off values can be found in *table 9.9* in appendix.

3.4.1 Definition of financial distress

Financial distress is a condition in which a company is unable to meet its financial obligations due to lack of income or liquid funds (Kenton, 2019; Bragg, 2019). The term financial distress is used in diverse contexts related to identification of failure, default, and bankruptcy (Pozzoli & Paolone, 2017). The bankruptcy prediction models of Ohlson, Altman and Zmijewski are primarily developed to predict bankruptcy (Reckers et al., 2003), but the respective models also classify companies as financially distressed or financially safe based on credit scores. The classifications of companies are used to conclude if a specific company is said to go bankrupt within a specific time horizon. In other words, if a company is classified as financially distressed, the models predict the company to go bankrupt within a defined timeframe. Reckers et al. (2003) states that there is a higher probability for distressed firms to go bankrupt but that most of the distressed firms do not go bankrupt.

3.4.2 Ohlson`s O-score model

A well-sited bankruptcy prediction model is Ohlson's O-score model, introduced in 1980 by James A. Ohlson. His model was the first of its kind by using conditional logit analysis to estimate a bankruptcy prediction model (Ohlson, 1980). In his estimation process Ohlson used a dataset containing financial information of U.S. firms from 1970-1976. The dataset was constructed of 105 bankrupt and 2058 non-bankrupt firms that were traded on exchanges. Based on this dataset, Ohlson created three different bankruptcy prediction models. Out of the models Ohlson estimated, the one that estimated bankruptcy one year prior to the incident had the highest accuracy, corresponding to 96.12 % (Ohlson, 1980).

Ohlson's O-score model is a nine-variable model for prediction of bankruptcy one year prior to the incident (Ohlson, 1980). Seven out of these nine variables are financial ratios for firm size, leverage, working capital, liquidity, profitability, change in net income and debt financing. The remaining two are dummies that are equal to 1 if a specific statement about the company's financial situation is true, and zero if the statement is false. Ohlson (1980) states that six of the variable were chosen based upon their presence in previous literature. If a company obtains an Ohlson score of less than 0.38 it is classified as not financially distressed, and if the Ohlson score is greater than 0.38 the company is classified as financially distressed. Based on a logistic transformation the Ohlson score can be transformed into probabilities (P) where $P < 0.50$ indicates a company in the safe zone and $P > 0.5$ indicates a company at risk and may default within one year (Ohlson, 1980). See *table 9.9* in appendix for a detailed explanation of the model.

3.4.3 Altman`s Z’’- score model

In 1968, one of the most well-known and applied bankruptcy prediction models was created by Edward I. Altman. His Z-score model (Altman, 1968), was estimated on a sample of 66 private US manufacturing corporations with a mean asset size of 6.4$ million. The model’s predictive ability to assign bankrupt and non-bankrupt firms into their respective groups was estimated to be 95% accurate (Altman, 1968). The Z’’- score model (Altman, 1983) is a re-estimated version of Altman’s Z-score model. Altman’s Z’’-Score model is a four-variable model for prediction of bankruptcy and was estimated to apply for both manufacturing and non-manufacturing firms (Altman, 2000). The model uses ratios of leverage, liquidity and profitability. If a company obtains an Altman score higher than 2.6 it is classified as financially safe, if the score is less than 1.1 it is classified as financially distressed. A score between 2.6 and 1.1 will classify the company as grey, with uncertain financial health.

According to Altman et al. (2014), the Z’’-Score model has been tested in at least 31 European countries and works consistently well internationally. Altman et al. (2014) re-estimated the Z’’-Score model on up-to-date country specific data, with new variables and other estimation methods. Their results indicated a prediction accuracy between 75% and 90% based on which country the model was tested in. They found that the classification accuracy could be improved with country specific estimation, but they also suggested that the original Z’’-Score model performs just as well as the new models in some countries.

3.4.4 Zmijewski`s X-score model

Probit analysis is another form of estimation procedure used to estimate a bankruptcy prediction model. Zmijewski (1984) was the first one to use this approach. He used a dataset with the entire population of US companies listed on the American and New York Stock Exchange in the period 1972-1978. In the estimation Zmijewski used 40 bankrupt and 800 non-bankrupt firms, and a holdout sample of 41 bankrupt and 800 non-bankrupt firms for prediction. His model uses financial ratios for financial performance, liquidity, and leverage, and were chosen based on their performance in previous studies. If a company obtains a Zmijewski score less than 0.50 the company is classified as financially safe, and if the Zmijewski score is greater than 0.50 it is classified as financially distressed. When the model was tested on the holdout sample Zmijewski obtained an accuracy rate of 70.7% for bankrupt firms and 99.5 % for non-bankrupt firms (Zmijewski, 1984).

When estimating the model, Zmijewski found that the current assets to current liabilities ratio was not statistically significant, and that according to a 99% significance level the only significant predictor would be net income to total assets. Shumway (2001) came to the same conclusion and argues that Zmijewski's model is a one variable model. Even though the generalizability of the Zmijewski model has not been proven, it is still widely used in the literature (Grice & Dugan, 2001). Grice & Dugan (2001) states that the model of Zmijewski is better suited for predicting financial distress than for predicting bankruptcy. At the same time, the X-score model of Zmijewski is not sensitive to different financial distress situations (Grice & Dugan, 2001).

3.4.5 Correspondence between Altman-score and Standard & Poor’s bond rating

In 1995, Altman, Hartzell & Peck estimated an emerging market version of the Altman Z’’-score model (Altman & Hotchkiss, 2006). A constant term of 3.25 was added to the model to standardize scores of 0 equal to D-rated bonds (Altman, 2000). We are going to use the emerging market model and add a constant of 3.25 to the Altman-scores for comparison of Altman-scores to Standard & Poor ratings presented in *table 3.5*. Mateev & Nightingale (2018) added the probability of default to every Standard & Poor rating grade, making it possible to interpret the probability of default of companies obtaining a specific Altman score. *Table 3.5* is a representation of Standard & Poor credit ratings, the thresholds estimated by Altman, Hartzell & Peck in 1995, and Mateev & Nightingale’s corresponding default probability (Altman & Hotchkiss, 2006).

Table 3.5*: Correspondence between Altman score and Standard & poor’s bond rating*

Rating	Threshold	Default probability (%)
AAA	> 8.15	0 - 0.25
AA+	8.15	0.25 - 0.37
AA	7.60	0.37 - 0.43
AA-	7.30	0.43 - 0.50
A+	7.00	0.50 - 0.62
A	6.85	0.62 - 0.79
A-	6.65	0.79 - 1.00
BBB+	6.40	1.00 - 1.19
BBB	6.25	1.19 - 1.73
BBB-	5.85	1.73 - 2.00
BB+	5.65	2.00 - 2.90
BB	5.25	2.90 - 3.56
BB-	4.95	3.56 - 4.00
B+	4.75	4.00 - 5.48
B	4.50	5.48 - 7.59
B-	4.15	7.59 - 10.00
CCC+	3.75	10.00 - 20.96
CCC	3.20	20.96 - 34.97
CCC-	2.50	34.97 - 50.00
D	< 1.75	> 50.00

3.5 Econometric techniques

3.5.1 Winsorization

The mean credit score and variance of the population is highly susceptible to score outliers. To minimize the influence of potential outliers in credit scores we used one of the most common approaches in finance, called winsorization (Adams, Haynga, Mansi, Reeb & Varardi, 2018). The winsorization technique removes outliers by setting extreme values to a specific percentile value. We performed a 96% winsorization, where all credit scores lower than the 2nd percentile were set to the 2nd percentile, and all scores higher than the 98th percentile were set to the 98th percentile. Dixon (1960) argues that winsorization improves the efficiency and increase the robustness of the statistical inference. He also states that the downside of bias is introduced, but this is less than if the data point had been deleted.

3.5.2 T-test and Wilcoxon's rank sum test

We assumed our sample of data and credit scores to be independent and identically distributed. For testing of statistically significant differences in our analysis we used t-tests. These tests were mainly unpaired independent two-sample t-test to compare the mean credit scores of the crowd borrowers and regular borrowers. We also performed Wilcoxon's rank sum test for comparison of score distribution and testing for whether there were differences in the median credit score.

Section 4 - Data

This section is divided into four parts, where section 4.1 describes the data and the data collection process. Section 4.2 highlights the cleaning and preparation steps performed to make the data ready for analysis. Thereafter, section 4.3 presents descriptive statistics of our dataset.

4.1 Data collection

In this thesis, a self-constructed dataset containing relevant descriptive and financial information of Norwegian crowdlending borrowers and corresponding control companies have been used. As crowdlending in Norway is a nascent industry, very little data exists. Therefore, we have manually created the dataset by mapping out the Norwegian crowdlending scene. This process involved finding all accepted Norwegian crowdlending borrowers and downloading relevant financial data from public databases. We have also downloaded large amounts of data to create a control group. The following sections will explain the data collection process in detail.

4.1.1 Data collection for Crowdlending borrowers

Basic information of crowdlending borrowers are openly available on the crowdlending platforms' websites. This information includes company legal name, loan sum, interest, loan date and credit scoring of the borrowers. Based on this information we have manually created a complete list of all Norwegian companies that have used crowd borrowing as a way of funding over the last four years. However, the data presented by the platforms is limited and insufficient for analysis purposes. We have therefore extracted accounting information for all crowdlending borrowers through the databases Proff.no and Proff Forvalt, owned by Proff AS (Proff, 2020). Proff.no is an online database containing financial information for Norwegian companies, and Proff Forvalt is an extended service of Proff.no that allows the user to segment and download large amounts of company data for analysis purposes. In total, the database contains data on more than 1,1 million Norwegian companies as of April 2020.

As explained in section 3.3.2, the variables age, county, NACE-code and company legal form were downloaded for each crowdlending borrower in order to perform the CEM procedure. Financial data was downloaded for the fiscal years 2015-2018, creating a panel data set that allowed us to perform a more precise CEM procedure, by matching on key financial variables in addition to the aforementioned variables.

A total of 125 Norwegian crowd borrowers were identified, which can be regarded as a surprisingly low amount spread over three crowdlending platforms. The limited number of borrowers could stem from several factors. First of all, the platforms are newly established, and have only been accepting loan applications for a few years. According to Rotem Shneor of the University of Agder, who collects market data on the Norwegian crowdlending market, no platforms were active prior to 2017 (Shneor, mentioned in Omreng & Gjendem 2017, p.35).

The platforms also claim to be very restrictive when reviewing loan applications. In June 2019, FundingPartner CEO Geir Atle Bore stated that out of the 1800 loan applications they had received, they had only accepted 26, giving an acceptance rate of 1.4% (Jordheim, 2019). As of May 2020, FundingPartner's acceptance rate has climbed to 1.88%, with 64 out of 3400 applications accepted (FundingPartner, n.d.). Ziegler et al. (2020) found that the average onboarding rate (share of loan applicants onboarded to the platform) in Europe was 18% for 2018, which is significantly higher than FundingPartner's 1.88%. The reputation and track record of the platform may be an important factor in this regard, as well-known platforms could likely attract higher-rated firms and thus keep a higher acceptance rate.

4.1.2 Data collection for the Control group

The control group was created using Proff Forvalt. Proff Forvalt's segmentation function allowed us to choose groups of companies based on NACE code and county and download these. A group corresponding with each crowdlending borrower's NACE code and county was downloaded. In total, the control group contains 57387 companies with key financial information between 2015-2018.

4.2 Data cleaning and preparation

To prepare the data for matching and analysis, we have cleaned and changed the structure of the dataset and created some additional variables for matching purposes. This section explains the necessary steps to prepare the data for matching and analysis.

To apply the Coarsened Exact Matching technique on the data sample, all of the data, both treatment and control variables, had to be combined into a singular data set. After combining the data, a dummy variable called "treatment" was created, with the value 1 for crowdlending borrowers and 0 for control companies. Furthermore, a variable calculating company age from date of establishment was created to allow it to function as a variable in the matching. The "age" variable was created using companies' date of establishment. For simplicity, companies established in 2017 were given age=3, 2016 were given age=4, and so on.

Proff Forvalt's segmentation tool does not allow the user to filter out companies that have missing values. We therefore cleared the data set of duplicate companies and observations with missing values. This is especially important as the matching technique and credit scoring models use different variables, thus possibly allowing the matching bins to include observations with missing values in key variables that would skew the credit scoring results. As a result, the sample of crowdlending borrowers was reduced from 88 to 79 observations, and the control group was reduced to 54657.

As described in section 3, we performed a k-to-k matching on the cleaned data sample, resulting in 67 matches with 67 crowd borrowers and 67 control companies. *Table 9.10* in appendix shows a short summary of key stats of our crowdlending borrowers and control companies before and after data preparation. In total, the number of crowdlending borrowers was reduced by 46% during data preparation. *Table 4.1* shows how the number of crowdlending borrowers in the sample was reduced through each step of the data procedure. Throughout the preprocessing and matching of the data sample, the number of crowdlending borrower was reduced from 125 to 67 borrowers.

Table 4.1*: Number of crowdlending borrowers left in each step of the data preprocessing and matching*

Stage	Number of crowdlending borrowers
Crowd borrowers identified	125
Data available at Proff Forvalt	88
After missing value removal	79
After matching	67

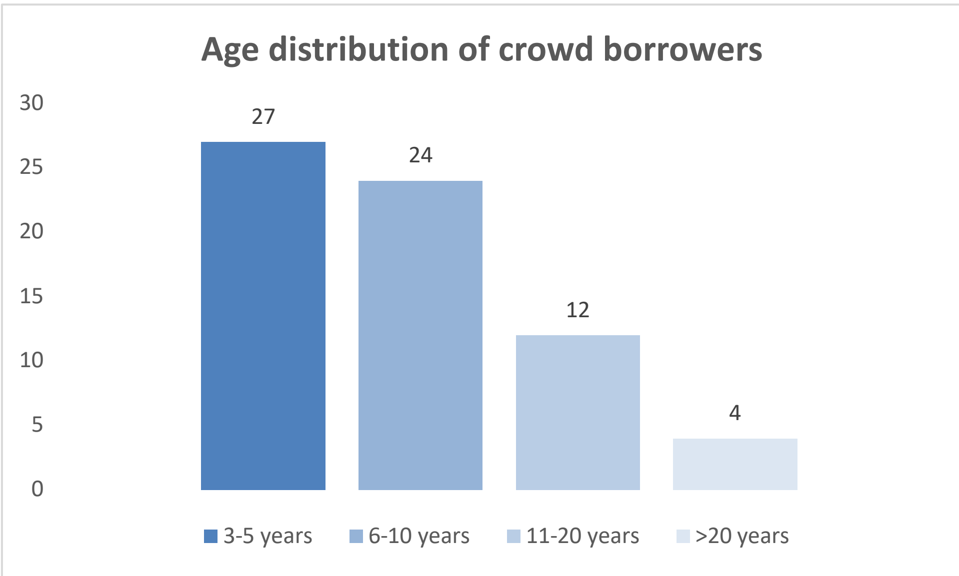
4.3 Descriptive statistics

In this section we will present statistics on key variables for the crowdlending borrowers, presented visually. The section aims at giving a better overview of key features of the treatment group.

4.3.1 Age

Figure 4.1 shows the 67 crowdlending borrowers divided by the age bins presented in section 3.3.2. A somewhat surprising fact may be that 23.9% of all crowd borrowers are over 10 years of age. As crowdfunding in general attracts many newly founded firms, one could expect the population of crowd borrowers to be younger than the data shows. However, the three Norwegian platforms are all enforcing a rule of minimum three years of age for all loan applicants. In addition to this, the previously discussed restrictiveness in loan application acceptance is also likely to lead to a higher age average amongst the accepted applicants.

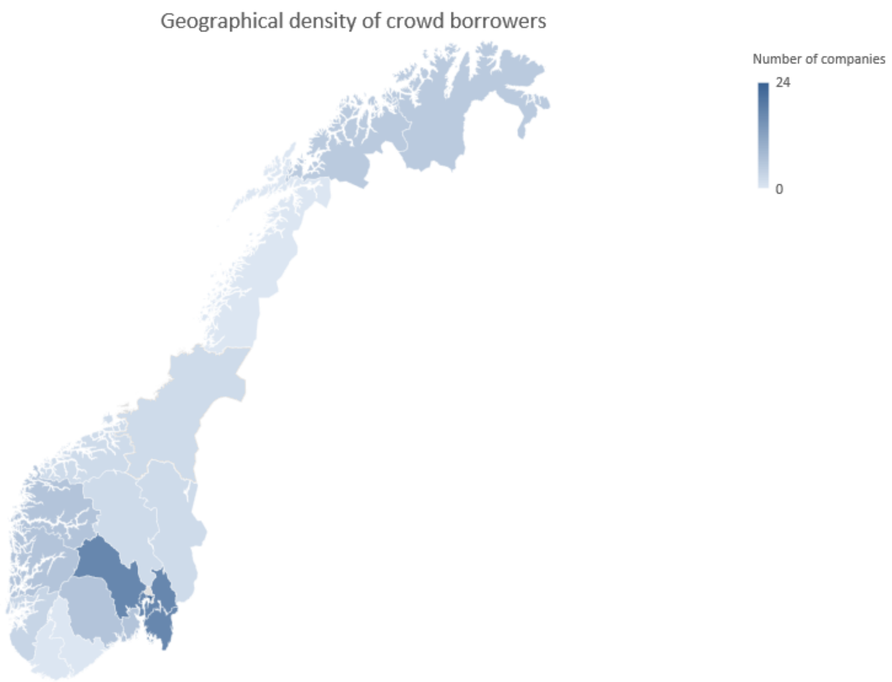
Figure 4.1: *Presentation of how many crowd borrowers that are in each age group*



4.3.2 Geography

Figure 4.2 maps out the crowdlending borrowers by county. The loan takers are spread across all 11 counties, but with a clear weight towards Eastern Norway, with 52 out of 67 companies located in Viken, Oslo, Innlandet and Vestfold and Telemark counties. This amounts to 77.6% of the total loan takers. Proff.no has roughly 54% of Norwegian companies registered in Eastern Norway, which means that this region has a disproportionately high representation in our crowd borrower group.

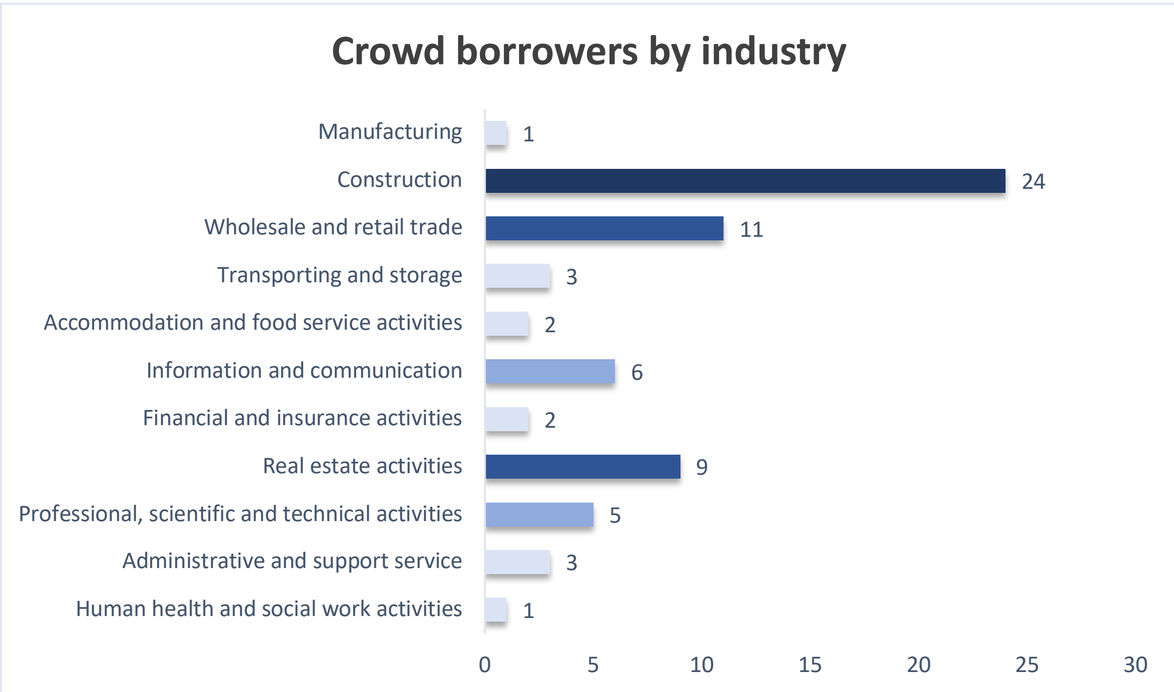
Figure 4.2: *Geographical density of crowd borrowers in Norway*



4.3.3 Industry

The 67 crowdlending borrowers are spread across 12 main industries, divided by NACE code. *Figure 4.3* shows how the loan takers are divided by industry. Of the 67 crowd borrowers, 33 are found under construction and real estate activities, amounting to 49.2%. The Norwegian real estate market has been highly profitable for years, with an average increase of 5.16% over the last 10 years (Pedersen, 2020). Of the 33 companies in construction and real estate, 17 belong under NACE code 41.109, "Development of Building Projects". An analysis of this industry gives a nationwide EBIT average of 16.71% in 2018 and 18.54% in 2017 (Proff Forvalt, 2020a). In other words, construction and real estate activities seem to be highly profitable industries in Norway, which might explain why many of these firms have been granted loans by crowdlending platforms.

Figure 4.3*: Distribution of the number crowd borrowers that are in each industry*



Section 5 - Empirical results

This section will provide the empirical results of our analysis on credit scores of companies taking up loans at crowdlending platforms in Norway (crowd borrowers), and matched control units from the general population of Norwegian companies (regular borrowers). Section 5.1 contains summary statistics of the credit scores of crowd borrowers and regular borrowers, as well as a presentation of the 10 best and worst rated crowd borrowers compared to Proff's credit rating. We will also present the corresponding Standard & Poor's credit rating of the crowd borrowers based on Altman scores. Section 5.2 contains an overview of the distribution of crowd borrowers and regular borrowers into financial distress categories and presents the financial health of crowdlending borrowers at the three platforms, Monner, FundingPartner, and Kameo. We finish off the empirical results section with the presentation of statistical tests in section 5.3. We conduct tests to see if there are differences in mean and median credit scores across crowdlending platforms, and test for significant differences in the mean and median credit scores for regular borrowers and crowd borrowers. Furthermore, we conduct tests against the credit models' cut-off scores to check whether the groups of borrowers are classified as financially healthy or unhealthy. Finally, we perform a linear regression to test the relationship between credit scores and interest rates. Our empirical results are discussed in more detail in section 6.

5.1 Summary statistics of credit scores

This section will provide summary statistics of the results of our credit scoring. We will present the mean and median scores of both the winsorized and unwinsorized dataset for the bankruptcy prediction models. We will also present a comparison of how the best and worst crowd borrowers perform in Proff's credit scoring system, and how our borrowers perform when converting their credit scores into Standard & Poor's ratings. The goal of this section is to give an overview of how the borrowers performed in our tests and provide comparisons to better understand what the scores indicate.

Table 5.1 presents summary statistics of the credit scores for the regular borrowers, crowd borrowers, and the entire sample. Each model contains original calculated credit scores, and a winsorized sample of scores. The winsorized data gives different mean credit scores for all models, but the median credit scores stay the same. The winsorization also results in a big reduction in the maximum scores and a small increase in the minimum score of crowd borrowers for all credit scoring models, and the standard deviation for credit scores is reduced by almost 50% for crowd borrowers. Looking at regular borrowers the standard deviation is slightly reduced (7% - 2%). The maximum credit scores are less reduced than for the crowd borrowers, but the lower scores seem to increase more for the Ohlson model and Zmijewski model. The mean credit scores for crowd borrowers seem to indicate less financial distress when outliers are removed. For the regular borrowers, the effects are more uncertain.

The statistics in *table 5.1* indicate that crowd borrowers are more financially distressed than regular borrowers. This statement is based on crowd borrowers having a higher mean Ohlson- and Zmijewski score than regular borrowers have, both for winsorized and unwinsorized score distributions. For the Altman model the score is higher for the regular borrowers in both samples. This indicates that regular borrowers are less financially distressed than crowd borrowers.

Table 5.1: *Summary statistics of credit scores for regular-, crowd-, and all borrowers*

Summary statistics for the credit-scoring models

Model	0 (N=67)	1 (N=67)	Overall (N=134)
Ohlson-score (1980)			
Mean (SD)	2.30 (3.73)	3.63 (7.53)	2.96 (5.96)
Median [Min, Max]	2.35 [-11.0, 14.4]	2.81 [-9.06, 56.2]	2.66 [-11.0, 56.2]
Ohlson-score (1980) (Winsorized)			
Mean (SD)	2.38 (3.47)	3.03 (3.63)	2.70 (3.55)
Median [Min, Max]	2.35 [-5.06, 14.4]	2.81 [-5.06, 15.5]	2.66 [-5.06, 15.5]
Altman-score (1983)			
Mean (SD)	2.33 (5.67)	1.21 (9.38)	1.77 (7.74)
Median [Min, Max]	2.09 [-16.4, 18.7]	1.25 [-46.8, 43.5]	1.60 [-46.8, 43.5]
Altman-score (1983) (Winsorized)			
Mean (SD)	2.22 (5.30)	1.39 (5.00)	1.80 (5.15)
Median [Min, Max]	2.09 [-15.3, 13.0]	1.25 [-15.3, 13.0]	1.60 [-15.3, 13.0]
Zmijewski-score (1984)			
Mean (SD)	0.153 (2.94)	1.41 (6.78)	0.784 (5.25)
Median [Min, Max]	0.126 [-6.31, 9.90]	0.821 [-4.63, 51.9]	0.595 [-6.31, 51.9]
Zmijewski-score (1984) (Winsorized)			
Mean (SD)	0.177 (2.88)	0.717 (2.52)	0.447 (2.71)
Median [Min, Max]	0.126 [-4.45, 9.62]	0.821 [-4.45, 9.62]	0.595 [-4.45, 9.62]

0 = Regular borrowers, 1 = Crowdlending borrowers, Overall = All borrowers, N = Number of borrowers

5.1.1 Credit scores and Proff.no credit ratings of best and worst crowd borrowers

In order to strengthen the robustness of our results, we wanted to compare our models' credit scoring with another credit scoring service. We identified the 10 best and worst rated crowd borrowers from each model and extracted their credit ratings from Proff Forvalt. This comparison indicates that there exists a correspondence between Proff's credit rating and the credit scores calculated based on Ohlson's-, Altman's-, and Zmijewski's model. The top 10 best rated borrowers based on all models are ranging from a Proff-rating from A2 to C1, with most of the borrowers in A and B ratings. Based on Proff (2020c), this is indicating low to moderate risk for the top-rated borrowers. If we look at the worst 10 borrowers, it is ranging from B2 to D with most of the companies in the C-scale. This indicates high to extremely high risk for the worst rated crowd borrowers (Proff Forvalt, 2020c).

Table 5.2.1: *Comparison of top- and worst-rated crowd borrowers with Proff's credit ratings.*

Ohlson (1980) model				
Rank	**Best rated**		**Worst rated**	
	Score	*Proff's rating*	*Score*	*Proff's rating*
1	-5.06	A2	15.45	
2	-5.06	B1	15.45	
3	-3.39	A3	15.45	
4	-2.24	A3	6.81	B2
5	-2.04	A2	6.31	
6	-1.15	A2	6.00	D
7	-0.74	B2	5.93	C2
8	-0,51	B1	5.93	C1
9	-0,46	C1	5.65	C2
10	0,29	B3	5.32	C1

Table 5.2.2: *Comparison of top- and worst-rated crowd borrowers with Proff's credit ratings.*

Altman (1983) model				
Rank	**Best rated**		**Worst rated**	
	Score	*Proff's rating*	*Score*	*Proff's rating*
1	12.97	A2	-15.26	
2	11.37	B1	-15.26	
3	10.09	A3	-5.76	D
4	10.04	A2	-5.44	B2
5	8.87	A3	-4.13	
6	8.33	A2	-4.10	C2
7	7.81	C1	-4.08	C1
8	6.87	B2	-3.89	C2
9	6.11	B3	-2.81	D
10	5.76		-2.77	C2

Table 5.2.3*: Comparison of top- and worst-rated crowd borrowers with Proff's credit ratings.*

Zmijewski (1984) model				
Rank	**Best rated**		**Worst rated**	
	Score	*Proff's rating*	*Score*	*Proff's rating*
1	-4.45	A2	9.63	
2	-4.45	B1	9.63	
3	-4.42	A3	4.27	
4	-3.69	A2	4.02	D
5	-3.32	A3	3.57	C2
6	-3.12	A2	3.23	C2
7	-2.96	C1	3.05	B2
8	-2.30	B2	3.02	D
9	-2.13	B1	2.88	C2
10	-1.55	B3	2.39	C1

5.1.2 Converting Altman scores into Standard & Poor's bond ratings

Credit scores based on Altman's Z''-score model can be converted into Standard & Poor's letter bond rating. We have added a constant term of 3.25 to our Altman scores to standardize the scores of 0 equal to D-rated bonds (Altman, 2000). For every letter rating there is a corresponding probability of default. We want to perform this comparison as the Standard & Poor's bond rating is a well-known and renowned bond rating standard and can give a better picture of the risks involved in crowdlending compared to bond investing. The results in *table 5.3* show that around one fifth of the crowd borrowers are rated as AAA, and approximately one third is rated as either D or CCC-. This indicates that around one third of the crowd borrowers have a probability of 34.97 % or higher to go default. At the same time one fifth of all crowd borrowers seem to have a financial situation that make them highly unlikely to default. For regular borrowers around 35 % are rated as AAA, and approximately 15% are rated either D or CCC-. This means that there are approximately twice as many crowd borrowers rated as either D or CCC- compared to regular borrowers. Based on the bond ratings for borrowers at different platforms it seems like they have approximately the same share of borrowers in AAA and the same share in CCC- and D.

Table 5.3: *Standard & Poor's bond rating of regular borrowers and crowd borrowers at different crowdlending platforms. See table 9.12 in appendix for a more detailed version*

				Crowd borrowers		Monner		FundingPartner		Kameo		Regular borrowers		
	Rating	**Threshold**	**Default probability (%)**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**	**Average values**
Safe	AAA	> 8.15	0 - 0.25	14	20.9 %	6	20.0 %	5	23.8 %	3	18.8 %	24	35.8 %	23.9 %
	AA+ to A-	6.65	0.25 - 1.00	9	13.4 %	5	16.7 %	2	9.5 %	3	18.8 %	3	4,5 %	12.6 %
	BBB+ & BBB	6.25	1.00 - 1.73	2	3.0 %	0	0.0 %	0	0.0 %	1	6.2 %	3	4.5 %	2.7 %
	Total			**25**	**37.3 %**	**11**	**36.7 %**	**7**	**33.3 %**	**7**	**43.8 %**	**30**	**44.8 %**	**39.2 %**
Grey	BBB- to B+	4.75	1.73 - 5.48	8	11.9 %	3	10.0 %	4	19.0 %	1	6.3 %	7	10.4 %	11.5 %
	Total			**8**	**11.9 %**	**3**	**10.0 %**	**4**	**19.0 %**	**1**	**6.3 %**	**7**	**10.4 %**	**11.5 %**
Distress	B & B-	4.15	5.48 - 10.00	4	6.0 %	1	3.3 %	1	4.8 %	2	12.5 %	11	16.5 %	8.6 %
	CCC+ & CCC	3.20	10.00 - 34.97	10	14.9 %	5	16.7%	3	14.3 %	2	12.5 %	9	13.4 %	14.4 %
	CCC- & D	< 1.75	> 34.97	20	29.8 %	10	33.3 %	6	28.5 %	4	25.0%	10	14.9 %	26.3 %
	Total			**34**	**50.7 %**	**16**	**53.3 %**	**10**	**47.6 %**	**8**	**50.0 %**	**30**	**44.8 %**	**49.3 %**
	TOTAL			**67**	**100.0 %**	**30**	**100.0 %**	**21**	**100.0 %**	**16**	**100.0 %**	**67**	**100.0 %**	**100.0 %**

5.2 Financial health of borrowers based on cut-off scores

In the following sections we will examine how the credit scores of crowd borrowers and regular borrowers are distributed across different financial distress zones. These distress zones are based on cut-off scores from the Ohlson-, Altman- and Zmijewski model and are designed to indicate whether or not companies are at risk of default. We will also look at how the companies are distributed into distress zones when divided into crowdlending platforms.

Table 5.4 is a numerical representation of how the groups of borrowers are distributed across the models' financial distress zones. The results show that 14.9 % of crowd borrowers are classified as safe based on the Ohlson model, 37.3 % based on the Altman model and 37.3 % for Zmijewski model. For the regular borrowers the corresponding shares are 29.9 %, 43.3 %, and 61.2 %. These numbers indicate that regular borrowers have a higher share in the safe zones and a lower share in the distress zones than crowd borrowers have.

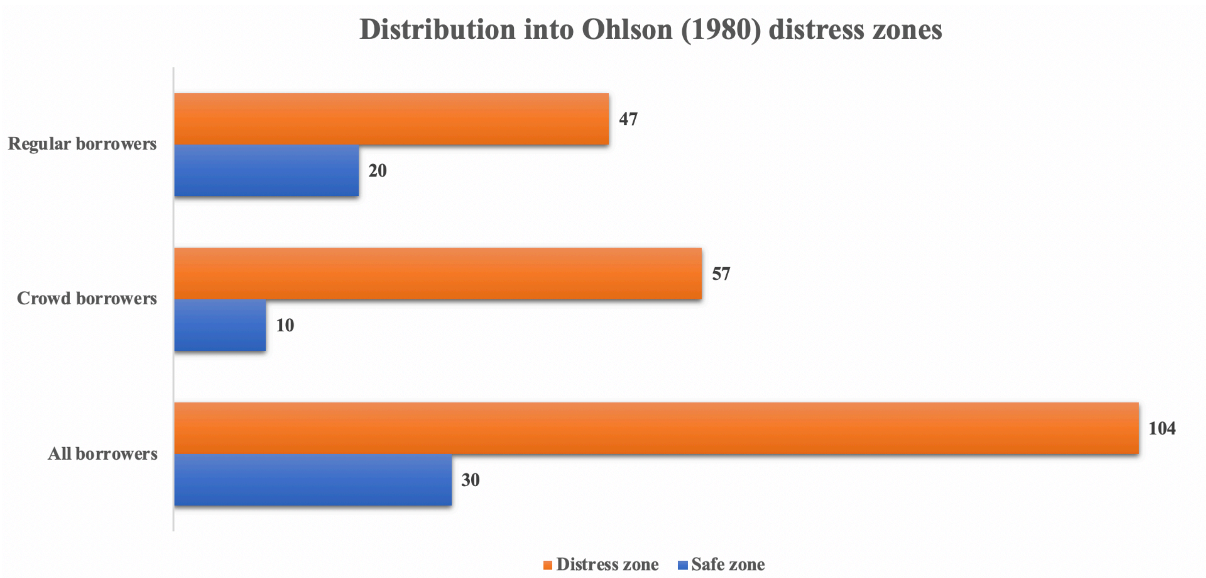
Table 5.4: *Percentage of all-, crowd- and regular borrowers in different financial distress zones.*

Borrowers	Ohlson (1980)		Altman (1983)			Zmijewski (1984)	
	Safe zone	Distress zone	Safe zone	Distress zone	Grey zone	Safe zone	Distress zone
All borrowers	22.4 %	77.6 %	40.3 %	45.5 %	14.2 %	49.3 %	50.7 %
Crowd borrowers	14.9 %	85.1 %	37.3 %	47.8 %	14.9 %	37.3 %	62.7 %
Regular borrowers	29.9 %	70.1 %	43.3 %	43.3 %	13.4 %	61.2 %	38.8 %

5.2.1 Ohlson's model

The Ohlson model operates with a *safe zone* and a *distress zone*. A credit score of less than 0.38 classifies a company as not financially distressed, and a score greater than 0.38 means it is financially distressed (Ohlson, 1980). *Figure 5.1* shows that the total population of borrowers is heavily skewed towards the distress zone. 85 % of crowd borrowers and 70 % of regular borrowers are in the distress zone, with a corresponding 15 % of crowd borrowers and 30 % of regular borrowers in the safe zone.

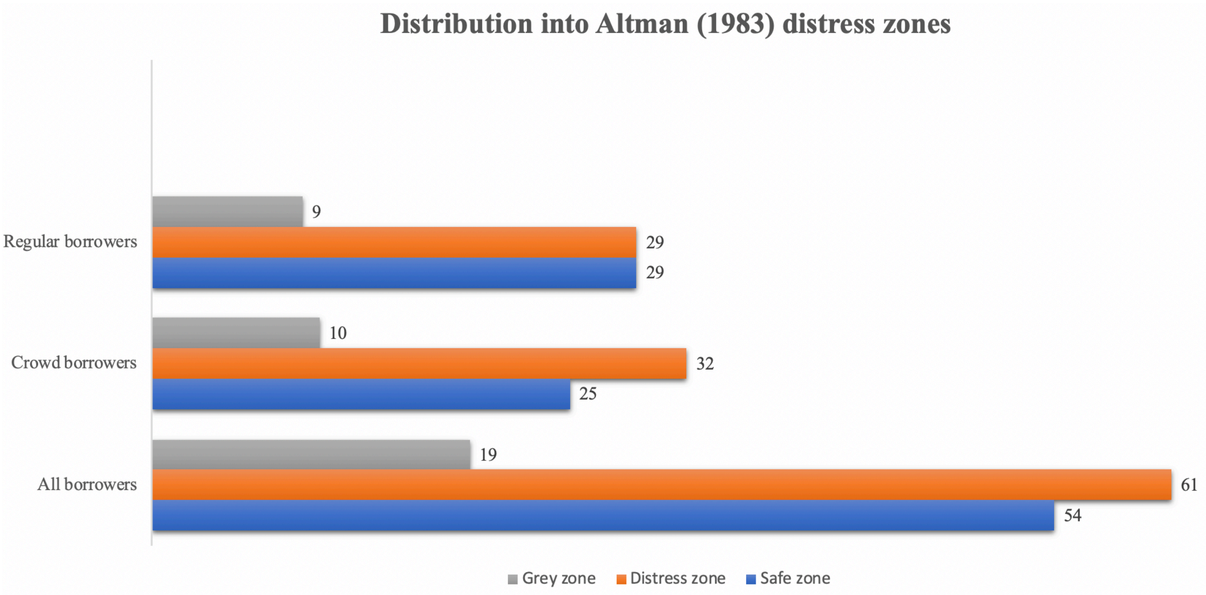
Figure 5.1*: Distribution of crowd borrowers and regular borrowers across distress zones created by Ohlson (1980)*



5.2.2 Altman's model

The Altman model operates with a *safe zone*, *grey zone*, and *distress zone*. A credit score of less than 1.1 classifies a company as distressed, a score between 1.1 and 2.6 classifies a company as in the grey zone, and a score higher than 2.6 classifies a company as in the safe zone (Altman, 1983). *Figure 5.2* indicates that a high propotion of borrowers experience some degree of financial distress, as the number of borrowers in the distress zone and grey zone account for 60%. The financially distressed companies seem to be evenly distributed between crowd borrowers and regular borrowers, with 42 crowd borrowers in the distress and grey zone, and corresponding 38 regular borrowers in the same zones. In other words, there seems to be little evidence to support that there are differences in the distress classification of crowd borrowers and regular borrowers based on results from the Altman model, as they have an approximate identical distribution.

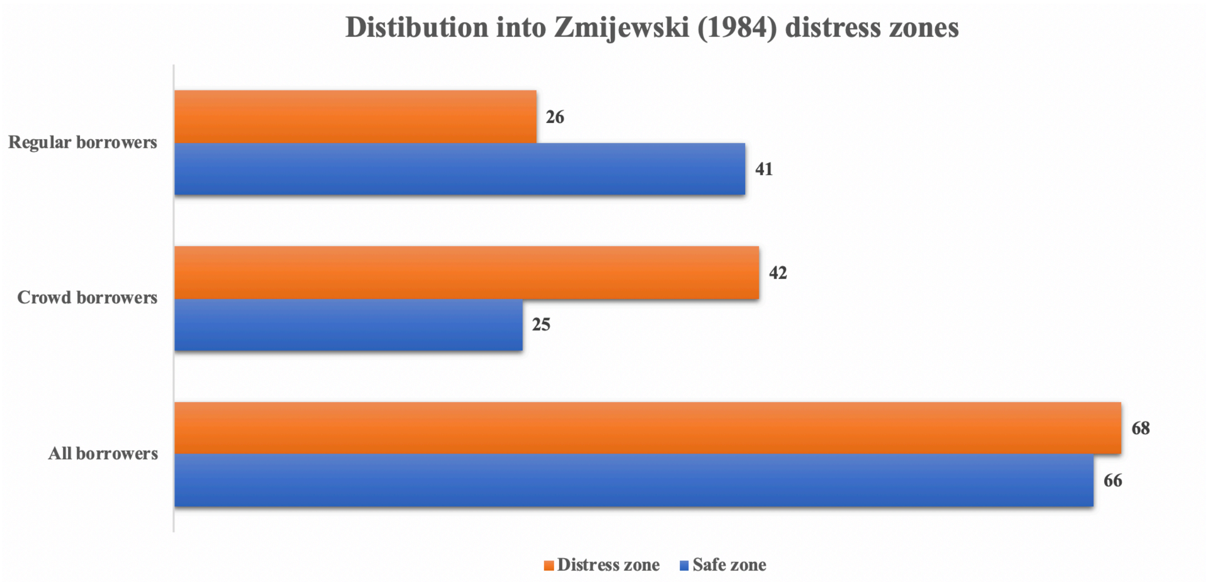
Figure 5.2: *Distribution of crowd borrowers and regular borrowers across distress zones created by Altman (1983)*



5.2.3 Zmijewski's model

Like the Ohlson-model the Zmijewski model operates with a *not financially distressed zone* (safe zone) and a *financially distressed zone* (distress zone). A credit score lower than 0.5 classifies a company as safe, and a credit score of 0.5 or higher classifies a company as financially distressed (Zmijewski, 1984). *Figure 5.3* is a representation of the distribution of borrowers into Zmijewski distress zones. Looking at the sample as a whole, the companies are quite evenly distributed into the safe zone and distress zone. However, the zone distributions of crowd borrowers and regular borrowers indicate that there are differences between the groups' financial distress levels, as the share of crowd borrowers in the distress zone is 24 percentage points higher than the share of regular borrowers.

***Figure 5.3**: Distribution of crowd borrowers and regular borrowers across distress zones created by Zmijewski (1984)*



5.2.4 Classification of financial health by platform

The crowd borrowers in our data sample have obtained loans at the Norwegian crowdlending platforms Monner, FundingPartner, and Kameo. After data preparation and matching there are 30 companies from Monner, 21 from FundingPartner and 16 from Kameo remaining in the data sample. *Table 5.5* represents the share of crowd borrowers from each platform in the respective distress zones. As the data shows, the distributions of the Altman model and Zmijewski model are relatively similar for each platform. The Ohlson model calculates a higher share of borrowers in the distress zone than the two other models. In general, there are larger shares of crowd borrowers that are classified as distressed than safe, except for the Zmijewski score calculated for crowd borrowers at the Kameo crowdlending platform. Here, the distribution between the safe zone and distress zone is even.

Table 5.5: *Distribution into distress zones for crowd borrowers at different crowdlending platforms*

Platforms	Ohlson (1980)		Altman (1983)			Zmijewski (1984)	
	Safe zone	Distress zone	Safe zone	Distress zone	Grey zone	Safe zone	Distress zone
Monner	13.3 %	86.7 %	36.7 %	53.3 %	10.0 %	33.3 %	66.7 %
FundingPartner	23.8 %	76.2 %	33.3 %	47.6 %	19.0 %	33.3 %	66.7 %
Kameo	6.3 %	93.8 %	43.8 %	37.5 %	18.8 %	50.0 %	50.0 %

5.3 Main empirical findings

In this section we will present a series of t-tests on our credit scoring results. First, we will test for differences in credit scores between the crowdlending platforms, Monner, FundingPartner and Kameo, to check if some platforms accept higher-risk borrowers than others. Then we will test credit scores agains the models' cut-off values, to see if we can classify the average borrower in the groups as financially safe or financially distressed. Lastly, we will test for differences in the mean and median credit scores of crowd borrowers and regular borrowers.

5.3.1 Differences in credit scores between crowdlending platforms

We perform tests to see if there are significant differences in credit scores between companies that have obtained loans at different crowdlending platforms. If the mean credit score of borrowers at one platform is found to be significantly worse than on another platform, it can indicate that a platform is taking higher risks with their borrowers. However, *Table 5.6* shows that there is no evidence to suggest a difference in credit scores between companies at different crowdlending platforms. This statement is true for every model.

Table 5.6*: T-tests of differences in credit scores between crowd borrowers at different crowdlending platforms*

Model	T-statistic	P-value	df
Monner vs FundingPartner			
Ohlson (1980)	0.576	0.568	49
Ohlson (1980) *winsorized*	0.092	0.927	49
Altman (1983)	-0.779	0.440	49
Altman (1983) *winsorized*	-0.239	0.812	49
Zmijewski (1984)	0.740	0.463	49
Zmijewski (1984) *winsorized*	0.548	0.586	49
Monner vs Kameo			
Ohlson (1980)	0.893	0.376	44
Ohlson (1980) *winsorized*	1.054	0.298	44
Altman (1983)	-0.733	0.468	44
Altman (1983) *winsorized*	-0.559	0.580	44
Zmijewski (1984)	0.823	0.414	44
Zmijewski (1984) *winsorized*	1.054	0.298	44
FundingPartner vs Kameo			
Ohlson (1980)	0.579	0.566	35
Ohlson (1980) *winsorized*	0.667	0.509	35
Altman (1983)	0.166	0.869	35
Altman (1983) *winsorized*	-0.268	0.790	35
Zmijewski (1984)	0.364	0.718	35
Zmijewski (1984) *winsorized*	0.185	0.855	35

Another approach is to use Wilcoxon's rank sum test to check for differences in credit scores between Norwegian crowd borrowers at different platforms. The tests check for differences in median credit scores, or that the distribution of credit scores differ. *Table 5.7* presents statistics from the Wilcoxon's rank sum tests. These results substantiates the results from the mean scores. There is no evidence to suggest that there are differences in the distribution of credit scores across the different crowdlending platforms. This result is valid for all bankruptcy prediction models applied.

***Table 5.7**: Wilcoxon's rank sum test for differences in distribution of credit scores between crowd borrowers at different crowdlending platforms*

Model	W-statistic	P-value
Monner vs FundingPartner		
Ohlson (1980)	1109	0.419
Ohlson (1980) *winsorized*	1107	0.426
Altman (1983)	301	0.798
Altman (1983) *winsorized*	301	0.798
Zmijewski (1984)	356	0.442
Zmijewski (1984) *winsorized*	356	0.442
Monner vs Kameo		
Ohlson (1980)	310	0.111
Ohlson (1980) *winsorized*	310	0.111
Altman (1983)	241	0,560
Altman (1983) *winsorized*	241	0.560
Zmijewski (1984)	291	0.247
Zmijewski (1984) *winsorized*	291	0.247
FundingPartner vs Kameo		
Ohlson (1980)	183	0.657
Ohlson (1980) *winsorized*	183	0.657
Altman (1983)	161	0.844
Altman (1983) *winsorized*	161	0.844
Zmijewski (1984)	179	0.751
Zmijewski (1984) *winsorized*	179	0.751

5.3.2 Differences in credit scores between borrower groups

We perform t-tests on the mean credit scores to check for statistically significant differences in scores between crowd borrowers and regular borrowers. The results are approximately the same regardless of which assumption is made about the groups' credit score variance. For simplicity we present the results assuming equal variance. Regardless of which model that is applied, the results from *table 5.8* give no evidence to suggest differences in mean credit scores between regular borrowers and crowd borrowers.

Table 5.8: *T-tests for differences in credit scores between crowd borrowers and regular borrowers*

Model	Average score	T-statistic	P-value	Variance
Ohlson (1980)	2.96	-1.299	0.196	equal
Crowd borrowers	3.63			
Regular borrowers	2.30			
Ohlson (1980) *winsorized*	2.70	-1.046	0.298	equal
Crowd borrowers	3.03			
Regular borrowers	2.38			
Altman (1983)	1.77	0.837	0.404	equal
Crowd borrowers	1.21			
Regular borrowers	2.33			
Altman (1983) *winsorized*	1.80	0.934	0.352	equal
Crowd borrowers	1.39			
Regular borrowers	2.22			
Zmijewski (1984)	0.78	-1.396	0.165	equal
Crowd borrowers	1.41			
Regular borrowers	0.15			
Zmijewski (1984) *winsorized*	0.45	-1.157	0.243	equal
Crowd borrowers	0.72			
Regular borrowers	0.18			

Table 5.9 shows the results from Wilcoxon rank sum tests. The results indicates a significant difference in the distribution of credit scores computed with Zmijewski's model. On the other hand, there are no significant differences when using Ohlson's or Altman's model. In summary the results regarding difference in the distribution of credit scores are inconclusive as the significance differs based on what credit scoring model that is used.

Table 5.9*: Wilcoxon's rank sum test for differences in the distribution of credit scores between crowd borrowers and regular borrowers*

Model	W-statistic	P-value
Ohlson (1980)	1907	0.134
Ohlson (1980) *winsorized*	1908	0.135
Altman (1983)	2603	0.111
Altman (1983) *winsorized*	2603	0.111
Zmijewski (1984)	1760	0.031*
Zmijewski (1984) *winsorized*	1762	0.032*

5.3.3 Testing credit scores against cut-off scores

In this section we will test whether the groups' mean credit scores are significantly different from the bankruptcy prediction models' cut-off values. The purpose of these tests is to check if it's possible to classify the groups of borrowers as financially distressed (unhealthy) or financially safe (healthy). Every table has three alternative hypotheses; *score less than limit*, *score greater than limit* and *score different from limit*. The null hypothesis is that the mean credit score is equal to the cut-off score.

Ohlson's cut-off score

As *table 5.10* shows, calculations based on the Ohlson model's cut-off score give results that classify both groups as within the financially distressed zone for the unwinsorized and winsorized data. This is consistent with the distribution presented in section 5.2.1, where 78.5% of all companies in the population are shown to be in the distress zone.

Table 5.10: *T-tests against cut-off scores based on Ohlson's model*

	Safe zone		Distress zone		Different from cut-off	
	Score less than 0.38		**Score greater than 0.38**		**Score different from 0.38**	
Model	**T-statistic**	**P-value**	**T-statistic**	**P-value**	**T-statistic**	**P-value**
Ohlson (1980)						
All borrowers	5.019	1	5.019	$8.18*10^{-7***}$	5.019	$1.64*10^{-6***}$
Crowd borrowers	3.532	0.99	3.532	$3.79*10^{-4***}$	3.532	$7.58*10^{-4***}$
Regular borrowers	4.206	1	4.206	$3.99*10^{-6***}$	4.206	$7.99*10^{-5***}$
Ohlson (1980) *winsorized*						
All borrowers	7.577	1	7.577	$2.69*10^{-12***}$	7.577	$5.37*10^{-12***}$
Crowd borrowers	5.963	1	5.963	$5.38*10^{-8***}$	5.963	$1.08*10^{-7***}$
Regular borrowers	4.730	1	4.730	$6.12*10^{-6***}$	4.730	$1.22*10^{-5***}$

Altman's cut-off scores

Table 5.11 shows test results of the average Altman scores against the Altman cut-off values. Both the unwinsorized and winsorized credit scores yield p-values higher than 0.50 when we test that the calculated scores are equal to 1.1. When testing an Altman-score of 2.6 against being in the safe zone the results yield p-values well above 0.50 for all borrower groups. This could indicate that all borrowers, regular borrowers and crowd borrowers are not classified as financially safe.

Table 5.11: *T-tests against cut-off scores based on Altman's model*

	Distress zone		Safe zone		Grey zone		Grey zone	
	Score less than 1.1		Score greater than 2.6		Score different from 1.1		Score different from 2.6	
Models	T-statistic	P-value	T-statistic	P-value	T-statistic	P-value	T-statistic	P-value
Altman (1983)								
All borrowers	1.007	0.842	-1.236	0.891	1.007	0.158	-1.236	0.109
Crowd borrowers	0.099	0.539	-1.210	0.885	0.099	0.461	-1.210	0.115
Regular borrowers	1.781	0.960	-0.384	0.649	1.781	0.04*	-0.384	0.351
Altman (1983) *winsorized*								
All borrowers	1.585	0.942	-1.790	0.962	1.585	0.058	-1.790	0.038*
Crowd borrowers	0.474	0.682	-1.984	0.974	0.474	0.319	-1.984	0.026*
Regular borrowers	1.731	0.956	-0.588	0.721	1.731	0.044*	-0.588	0.279

The winsorized scores of crowd borrowers and the population as a whole are significantly different from the upper limit on a 95 % level. Further on, we cannot reject that the unwinsorized scores for these groups are equal to or below 2.6, although the low p-values suggest a credit score in the lower part of the grey zone (1.1-2.6). As for the regular borrower scores, the tests allow us to reject a hypothesis that the score is equal to 1.1 for both the unwinsorized and winsorized dataset. At the same time, it is not possible to reject that the credit score for regular borrowers are different from the upper limit, thus stating that the mean score is situated in the gray or safe zone.

Zmijewski's cut-off score

Table 5.12 shows test results of the average Zmijewski scores against the Zmijeski cut-off value. The results provide no evidence to reject that the credit scores of crowd borrowers and regular borrowers are different from a score of 0.5. The p-values closest to rejection for the crowd borrowers occur when tested with an alternative hypothesis of the score being greater than the cut-off, and for regular borrowers with an alternative hypothesis that the score is lower than the cut-off. This is consistent with their mean scores of 1.41 and 0.15 for crowd borrowers and regular borrowers respectively. In other words, the groups seem to be on opposite ends on the scale, but the difference between them is still not statistically significant as shown in *table 5.8*.

Table 5.12: *T-tests against cut-off scores based on Zmijewski's model*

	Safe zone		**Distress zone**		**Different from cut-off**	
	Score less than 0.5		**Score greater than 0.5**		**Score different from 0.5**	
Model	**T-statistic**	**P-value**	**T-statistic**	**P-value**	**T-statistic**	**P-value**
Zmijewski (1984)						
All borrowers	0.626	0.734	0.626	0.266	0.6256	0.534
Crowd borrowers	1.103	0.863	1.103	0.137	1.103	0.274
Regular borrowers	-0.965	0.169	-0.965	0.831	-0.965	0.338
Zmijewski (1984) *winsorized*						
All borrowers	-0.228	0.410	-0.228	0.590	-0.228	0.820
Crowd borrowers	0.706	0.759	0.706	0.241	0.706	0.483
Regular borrowers	-0.920	0.180	-0.920	0.820	-0.920	0.361

5.3.4 Comparison of credit ratings and interest rates

We perform linear regressions to see if there is a relationship between the borrowers' interest rates and our calculated credit scores. *Table 5.13* shows the outputs of the regressions where the credit scores are added as variables to explain the interest rates paid by borrowers. For the Ohlson- and Zmijewski scores the coefficients ("Credit score") are positive meaning that there is a positive relationship between the interest rate and the credit scores. In other words, a higher Ohlson- and Zmijewski score is related to a higher interest rate. This is consistent with expectations, as higher Ohlson- and Zmijewski scores indicate higher risk. The Altman score has a negative coefficient, which is also consistent with expectations as a higher Altman score indicate lower risk. However, none of the coefficients are statistically significant.

Table 5.13: *Regression results – Linear regression of borrowers' interest rate on crowdlending loans on corresponding credit scores from the bankruptcy prediction models made by Ohlson, Altman and Zmijewski.*

	Ohlson		**Altman**		**Zmijewski**	
	Normal	**Winsorized**	**Normal**	**Winsorized**	**Normal**	**Winsorized**
Constant	9.639***	9.536***	9.748***	9.775***	9.689***	9.646***
	(0.172)	(0.201)	(0.154)	(0.160)	(0.159)	(0.159)
Credit score	0.021	0.060	-0.026	-0.042	0.0195	0.099
	(0.020)	(0.043)	(0.016)	(0.031)	(0.023)	(0.061)
P-value	0.308	0.167	0.117	0.182	0.40	0.111
R^2	0.016	0.029	0.038	0.027	0.01	0.039
Adjusted R^2	0.001	0.014	0.023	0.012	-0.004	0.024
No. Observations	67	67	67	67	67	67

Standard errors are reported in the parentheses.
*Statistical significance: *** $p<0.001$ and ** $p<0.05$*

Section 6 - Discussion

This thesis examines the financial health of borrowers at Norwegian crowdlending platforms. We believe it is important to shed light on this topic because of crowdlending's rising popularity in Norway, Europe, and all over the world. Additionally, it is an important topic because of its potential substitution for traditional bank lending. In this section, our main empirical findings will be discussed in light of theoretical elements in previous literature. In this section we discuss or findings in detail. Section 6.1 discusses how the platforms target different borrower segments, and section 6.2 presents a discussion of the financial health of Norwegian crowd borrowers compared to similar Norwegian companies. Section 6.3 discusses the accuracy of our bankruptcy prediction models, and section 6.4 explores the economic consequences of having an underserved credit market.

6.1 Discussing crowdlending platforms' target markets

Standard & Poor's ratings suggest that there are approximately equal shares of borrowers in the top and bottom rating categories across Monner, FundingPartner and Kameo. This substantiates the claim that platforms attract healthy borrowers due to attractive traits of the borrowing process (Moreno-Moreno et al., (2018), and that banks potentially underserve a market of financially healthy borrowers (Hetland et al., 2017), leading healthy borrowers to alternative financing sources such as crowdlending platforms. At the same time platforms distribute loans to a large share of financially unhealthy companies, meaning that they also target borrowers that probably would have problems obtaining loans in traditional banks. In other words, the platforms are able to attract healthy borrowers, but they are also distributing loans to unhealthy borrowers. Our results also show that the platforms accept borrowers of the same financial health.

The marginal cost of setting up an investor account at a crowdlending platform is close to zero, but the fixed cost of creating a platform is substantial. Consequently, platforms need a large market with a high number of users to be profitable (Lenz, 2016). Based on 2018 financial data from Proff.no, Monner (Proff, 2018a), FundingPartner (Proff, 2018b), and Kameo (Proff, 2018c) are not profitable. Furthermore, the business model of crowdlending platforms is such that the risk is decentralized, spreading the risk to investors. The platforms thus have an incentive to maximize the number of loans given, as both repaid and defaulted loans yield the platform revenue. It will therefore be in the platforms' interest to distribute loans to both healthy and unhealthy borrowers, and our findings indicate that they are doing this to some extent.

6.2 Discussing the financial health of crowd borrowers

Our findings yield no evidence for a significant difference in the financial health between Norwegian companies obtaining loans at crowdlending platforms, and relatively similar Norwegian companies. These findings are valid across the Ohlson-, Zmijewski-, and Altman model. A normal expectation could be that adverse selection would give a situation where financial healthy companies obtain loans in banks, and unhealthy companies use crowdlending platforms (Lenz, 2016). Our findings match the findings of Lenz (2016), who argues that it is not possible to validate this segmentation of credit risk between banks and platforms.

Further this could indicate that banks are underserving the credit market by refusing loans to a customer segment that is equipped to service high interest rates. This effect may be a consequence of companies being met with strict rules from traditional banks after the financial crisis of 2008 (Moreno-Moreno et al., 2018). There has been a drop in available credit in Norway for specific segments of borrowers, and the proportion of companies that take up bank loans in Norway have fallen steadily from 48% to 32% (Hetland et al., 2017). Hetland et al., (2017) also argue that small, young Norwegian growth companies have experienced a reduced access to bank loans after the financial crisis. Furthermore, the more restrictive banks are, the better financial health we would assume to find in the group of traditional borrowers. This could implicitly lead to an observation of higher financial health of the group of crowd borrowers.

Moreno-Moreno et al. (2018) argue that the growing popularity of crowdlending could be due to the fact that crowdlending reduces transaction costs and connects lots of people to a given project. The favourable traits of the borrowing process attract borrowers that are rejected by banks, but high-quality borrowers could also find this attractive (Moreno-Moreno et al., 2018).

6.3 The accuracy of our bankruptcy prediction models

Although our bankruptcy prediction models disagree about the financial health of our crowd borrowers, they all predict a substantial amount to go bankrupt within a year. The Ohlson model predicts a default rate of 85.1%, the Altman model predicts a default rate of 47.8% and the Zmijewski model's number is 62.7%. In this section we will compare these predictions with the actual loan default and bankruptcy rates of our crowd borrowers and discuss why they are so different.

Based on the high default probability predictions we would expect the loan default rate on the crowdlending platforms to be substantial. However, Jordheim (2020) states that only 3.7% of the loans from Norwegian crowdlending platforms have defaulted. Of these there are 0 at FundingPartner, 4 at Monner and 6 at Kameo. The default rate is far off the predicted default rates of our models, but at the same time there is a high number of outstanding loans, and the true default rate is not yet clear. FundingPartner, Kameo, and Monner have accepted 49, 213 and 105 loans respectively per January 10th, 2020, but only 6, 137 and 13 loans had been fully repaid (Jordheim, 2020).

Based on data from Brønnøysundregistrene (2020b), there are no cases of bankruptcy among the crowd borrowers in our sample as of June 4th, 2020. Although the true default rate is not yet clear, this further indicates that the models' predictions are highly unlikely to come true. Reckers et al. (2003) argue that bankruptcy prediction models are better at predicting economic hardship than they are at predicting bankruptcies, and that most firms in distress will not declare bankruptcy. Our findings may support this.

6.4 Effects of an underserved credit market

Although our results are inconclusive, they could indicate that banks are underserving the credit market by refusing loans to a customer segment that is equipped to service high interest rates. The effects of an underserved credit market on the economy has been subject to several studies and is well documented in the literature. This section will highlight some of the more prominent studies on underserved credit markets and discuss the implications of our results in light of these studies.

Ferrando and Mulier (2015) analyze the economic effects of “discouraged borrowers”, which are firms that need external finance, but do not apply for bank loans due to the fear of being rejected. They find that being discouraged from applying for bank loans has a negative effect on the firm’s investment growth, employment, and asset growth. Buca and Vermeulen (2017) further argue that credit tightening by banks lead to reduced aggregate investment in the economy. Studying the credit market in six European countries over five years, they find that industries who are depending on banks for their credit reduced investment to a much larger extent than in non-dependent industries. García-Posada (2018) backs this up, finding evidence to suggest that financial constraints cause businesses to reduce investment. The studies thus provide compelling evidence on how a diversification on the supply side of the credit market can help the real economy stay healthy.

In summary, the negative effects of underserving credit institutions on the economy are well documented in the literature, and governing authorities are incentivized to mitigate these effects. Crowdlending regulations should therefore aid crowdlending platforms in supplying the credit market rather than hinder it. Today there are several regulatory measures imposed on the Norwegian market, like described in section 2.2.2, that can be said to hinder crowdlending growth. Norwegian platforms will hope that their solid growth and track record so far can help lawmakers realize that crowdlending is improving the credit market rather than impeding it, which in turn could lead to a loosening of the strict regulations.

Section 7 - Limitations

This section will highlight the limitations of our thesis. We will discuss possible weaknesses regarding our dataset, data collection, matching method, and the bankruptcy prediction models that have been used. Section 7.1 discusses limitations of the collection and preprocessing of the data. Section 7.2 discusses the matching method and sample size, and section 7.3 presents limitations of the bankruptcy prediction models.

7.1 Collection and preprocessing of data

As our collection and preprocessing of data was manually handled, the likelihood of having performed errors is present. The following segment discusses some of the errors that might have occurred, and what this could mean for the analysis.

Our dataset was manually constructed using Proff Forvalt's segmentation tool. This means that the sample of data, and thus the analysis, relies on the accuracy of the Proff.no database. Proff.no gets their data directly from Brønnøysundregistrene (Proff Forvalt, 2020b), which is a Norwegian government agency that handles various public records. Norwegian companies are required to send accurate financial statements to Brønnøysundregistrene each year (Brønnøysundregistrene, 2020a). Based on this information, we consider the data from Proff.no to possess a high degree of accuracy. Still, this does not guarantee that the data is free of errors, which could possibly skew our results.

Another possible issue stems from the manual data collection and preprocessing. The process of manually searching up all identified crowd borrowers on Proff.no and downloading their data leaves room for error, although the accuracy of the process has been controlled multiple times. A large part of the data preprocessing and the analysis have been performed by programming in Excel and R-studio. There may have been errors in the writing and processing of the code. The code has been checked for errors multiple times and discovered errors have been fixed.

When sampling our control group, we assumed that companies with net positive total liabilities were companies that had obtained loans in traditional banks. This assumption does not necessarily hold for all companies, as a company could potentially have no debt to traditional banks, but instead have liabilities to other institutions, accounts payable, or just short-term debts.

7.2 Matching and sample size

As described in section 3.2, the Coarsened Exact Matching procedure was chosen due to its ability to perform better than similar matching techniques on bias, estimation error and imbalance reduction. Despite this, the matching procedure has limitations. This section discusses some of these.

Iacus et al. (2012) argue that Coarsened Exact Matching is a method that improves causal inference and possesses a wide range of desirable statistical properties not available in most other matching methods. Despite these favourable properties, the matching procedure does not guarantee complete randomness of our sample, but rather tries to approach randomness. An important feature of the CEM procedure is the ability to choose our own bin sizes. In other words, the level of imbalance can be controlled by increasing or reducing bin sizes. In our selection of bin sizes, we have not chosen to maximize imbalance reduction, but chosen bin sizes that reflect real-life classifications, like the NACE industry codes and the European Commission's business size classification. The data therefore possesses some degree of imbalance, although it was reduced through matching.

Another effect of using the k-to-k matching is that we were left with relatively few observations, with 67 crowd borrowers and 67 regular borrowers. This may have resulted in a selection bias in our dataset. Selection bias occurs when groups in a study differ systematically from the population of interest (Nunan, Bankhead, Aronson, 2017). We chose to use the total assets and total liabilities data from 2017 in our matching to reduce imbalance, which may have filtered out the newest and least established companies from the sample. Borch et al. (2002) find that both small and newly established companies have higher risk of going bankrupt, meaning that filtering out the newly established firms will likely have raised the mean credit score of the sample. The effect might be that our results are not representative of the target population.

In our analysis we found few significant results. Based on summary statistics it looked like there were a difference between crowd borrowers and regular borrowers based on mean credit score for all models. There was also a higher proportion of crowd borrowers that were classified as financially distressed in all models. Because of few observations the variance of the credit scores was high. Ioannidis (2005) states that research findings are less likely to be true the smaller the sample size is. Our low number of observations and high variance is therefore a source of uncertainty in our findings and indicates that our conclusions should be viewed with caution.

7.3 Bankruptcy prediction models

Ohlson's, Altman's, and Zmijewski's bankruptcy prediction models yield no difference in credit scores between the two groups of borrowers. However, the classification of borrowers into a financial health category varies between the three bankruptcy prediction models. The vastly different results indicate that some or all of the models are inaccurate.

Our choice of bankruptcy prediction models was based upon previous results and prediction accuracy in literature. The models are mentioned in most well-known literature review papers regarding credit scoring and bankruptcy prediction. Several papers, including Balcaen & Ooghe (2006) and Bellovary et al. (2007) report a high prediction accuracy for these models in different markets and countries. However, the lack of qualitative information in the credit scoring process means we omit potentially important information in the assessment of crowd borrowers. An optimal solution for assessing credit quality of crowd borrowers should be to incorporate qualitative information in the process of evaluation.

We have chosen bankruptcy prediction models that have been tested in multiple countries and industries with good results. However, the lack of a country specific bankruptcy prediction models is a potential weakness in our analysis. Different credit scoring models have been proven to vary a lot regarding prediction accuracy across different countries. For instance, Altman (2014) found that the Altman Z''-model performed worse in Norway compared to countries like Sweden, China and Russia. The models' authors found that a certain portion of firms that was classified as distressed was actually healthy, with probabilities of this happening ranging from 14-25% (Ohlson, 1980; Zmijewski, 1984; Altman & Hotchkiss, 2006).

In summary, we must keep in mind that these models are predictive, and only give an indication of the financial health of a company and its potential of going bankrupt based on general criteria.

Section 8 – Conclusion

In this thesis we have examined whether Norwegian companies that have obtained loans at crowdlending platforms are riskier than borrowers in traditional banks, and thus have higher probability to go bankrupt or default on loans. We have applied three proven bankruptcy prediction models to a dataset of Norwegian crowd borrowers and similarly matched Norwegian companies to calculate their financial health. Based on our analysis, we do not find any evidence to suggest that the credit quality of crowd borrowers and borrowers in traditional banks are significantly different, even though the mean and median credit scores of the crowd borrower group are worse for all models. Results from our analysis also show that a large group of both crowd borrowers and regular borrowers are classified as financially distressed across all three models, meaning that our sample of businesses are skewed towards having a larger portion with low credit quality than with high credit quality.

We also analysed differences in credit quality of crowd borrowers at the Norwegian crowdlending platforms Monner, FundingPartner, and Kameo. There is no evidence suggesting that any of the platforms take on higher risk borrowers than the others. The platforms attract both high-quality and low-quality borrowers, with 30% of borrowers in the highest credit rating (AAA) and 50% in the lowest ratings (CCC- & D) based on the Altman scores converted to Standard & Poor's bond rating. The high number of high-rated crowd borrowers could indicate that traditional banks are underserving the credit market by refusing loans to a customer segment that is equipped to service high interest rates. An alternative explanation could be that crowdlending possesses favourable traits that high rated borrowers may find attractive.

Section 9 – Appendix

9.1 Robustness

To check the robustness of the matching approach, Coarsened Exact Matching, and the corresponding results, we changed the bin sizes of age, assets, and liabilities. The bins of the age variable were altered into the following intervals: 0-3. 4-5, 6-7, 8-10, 11-15, 16-20 and over 20 years old. This change lead to a reduction in the number of matched borrowers from 67 to 62 companies in each borrower group, and we obtained an imbalance score of 0.339, slightly better than the original k-to-k solution (0.379). The calculated credit scores based on this sample of borrowers gave the same results as our main analysis. There were no significant differences in financial health between Norwegian crowdlending borrowers and relatively similar Norwegian companies. The results are presented in table 9.1 and table 9.2.

Table 9.1: *T-test for differenced in credit scores with new bins and bin sizes regarding age*

Model	Average score	T-statistic	P-value	Variance
Ohlson (1980)		0.7731	0.441	equal
Crowd borrowers	3.71			
Regular borrowers	5.09			
Ohlson (1980) *winsorized*		0.8526	0.396	equal
Crowd borrowers	3.30			
Regular borrowers	4.20			
Altman (1983)		0.9943	0.322	equal
Crowd borrowers	1.13			
Regular borrowers	67.6			
Altman (1983) *winsorized*		-0.0471	0.962	equal
Crowd borrowers	1.17			
Regular borrowers	1.10			
Zmijewski (1984)		0.1309	0.896	equal
Crowd borrowers	1.48			
Regular borrowers	1.34			
Zmijewski (1984) *winsorized*		0.6160	0.539	equal
Crowd borrowers	0.88			
Regular borrowers	1.31			

Table 9.2: *Wilcoxon's rank sum test for differences in credit scores with new bins and bin sizes regarding age*

Model	W-statistic	P-value
Ohlson (1980)	1892	0.883
Ohlson (1980) *winsorized*	1891	0.789
Altman (1983)	2063	0.483
Altman (1983) *winsorized*	2063	0.483
Zmijewski (1984)	1770	0.449
Zmijewski (1984) *winsorized*	1771	0.452

Secondly, we changed the bins of assets into the intervals presented in the left side of *table 9.3.* The new matching solution gave a sample of 60 matched crowd borrowers and 60 regular borrowers, and the imbalance was increased to 0.450. The change in asset intervals gave no difference in the results of the analysis, as shown in appendix *table 9.4* and *table 9.5*. Finally, we changed the bins of total liabilities into the intervals presented in the right side *of table 9.3.* The new matching lead to 65 matched crowd borrowers and 65 regular borrowers with a corresponding imbalance of 0.338. The results gave no evidence of a significant difference in the financial health of crowd borrowers and regular borrowers. In summary, our results are robust to changes in the coarsening of the matching variables.

Table 9.3*: New bins and bin sizes for total assets(2017) and total liabilities(2017)*

Bins	Total assets (NOK 2017)
1	-10 000 000,- to - 1 000 000,-
2	-999 999,- to -550 000,-
3	-549 999,- to 0,-
4	1,- to 100 000,-
5	100 001,- to 1 000 000,-
6	1 000 001,- to 5 000 000,-
7	5 000 001,- to 10 000 000,-
8	10 000 001,- to 93 295 000,-
9	93 295 001,- to 401 168 000,-
10	> 401 168 000,-

Bins	Total liabilities (NOK 2017)
1	< 0,-
2	0,- to 500 000,-
3	500 001,- to 999 999,-
4	1 000 000,- to 1 999 999,-
5	2 000 000,- to 4 999 999,-
6	5 000 000,- to 9 999 999,-
7	10 000 000,- to 29 999 999,-
8	30 000 000,- to 49 999 999,-
9	> 50 000 000,-

Table 9.4: *Wilcoxon's rank sum test for differences in credit scores with new bins and bin sizes regarding total assets (2017)*

Model	W-statistic	P-value
Ohlson (1980)	1620	0.346
Ohlson (1980) *winsorized*	1621	0.349
Altman (1983)	1993	0.312
Altman (1983) *winsorized*	1993	0.312
Zmijewski (1984)	1525	0.150
Zmijewski (1984) *winsorized*	1525	0.150

Table 9.5: *T-test for differences in credit scores with new bins and bin sizes for total assets (2017)*

Model	Average score	T-statistic	P-value	Variance
Ohlson (1980)		0.883	0.379	equal
Crowd borrowers	3.71			
Regular borrowers	11.9			
Ohlson (1980) *winsorized*		-0.150	0.881	equal
Crowd borrowers	3.22			
Regular borrowers	3.09			
Altman (1983)		-0.405	0.686	equal
Crowd borrowers	1.13			
Regular borrowers	-3.95			
Altman (1983) *winsorized*		0.506	0.614	equal
Crowd borrowers	1.09			
Regular borrowers	1.82			
Zmijewski (1984)		0.416	0.817	equal
Crowd borrowers	1.52			
Regular borrowers	6.83			
Zmijewski (1984) *winsorized*		-0.348	0.729	equal
Crowd borrowers	0.89			
Regular borrowers	0.67			

Table 9.6: *Wilcoxon's rank sum test for differences in credit scores with new bins and bin sizes for total liabilities (2017)*

Model	W-statistic	P-value
Ohlson (1980)	1913	0.354
Ohlson (1980) *winsorized*	1913	0.354
Altman (1983)	2442	0.126
Altman (1983) *winsorized*	2442	0.126
Zmijewski (1984)	1729	0.075
Zmijewski (1984) *winsorized*	1730	0.075

Table 9.7*: T-test for differenced in credit scores with new bins and bin sizes for total liabilities(2017)*

Model	Average score	T-statistic	P-value	Variance
Ohlson (1980)		-0.373	0.710	equal
Crowd borrowers	3.72			
Regular borrowers	3.24			
Ohlson (1980) *winsorized*		-0.392	0.696	equal
Crowd borrowers	3.15			
Regular borrowers	2.85			
Altman (1983)		1.152	0.252	equal
Crowd borrowers	1.13			
Regular borrowers	6.44			
Altman (1983) *winsorized*		0.999	0.319	equal
Crowd borrowers	1.31			
Regular borrowers	2.53			
Zmijewski (1984)		-0.568	0.570	equal
Crowd borrowers	1.48			
Regular borrowers	0.84			
Zmijewski (1984) *winsorized*		-0.739	0.461	equal
Crowd borrowers	0.82			
Regular borrowers	0.42			

9.2 Imbalance score pre- and post-matching

Table 9.8: *Imbalance measure pre- and post-matching and with k-to-k matching*

Imbalance measure	
Pre-matching	0.903
Automatic matching	0.940
k-to-k matching	0.379

9.3 Summary of the bankruptcy prediction models

Table 9.9*: Summary of the bankruptcy prediction models we have applied, the mathematical formulation , variables and description of ratios. See table 9.11 for an explanation of the abbreviations*

Model	Formula	Variable	Description
Ohlson (1980)	Ohlson score = $- 1.32 - 0.407\log(X^1) + 6.03X^2$	X^1	TA/GNP
	$- 1.43X^3 + 0.0757X^4 - 2.37X^5$	X^2	TL/TA
	$- 1.83X^6 + 0.285X - 1.72Y - 0.521X^9$	X^3	WC/TA
		X^4	CL/CA
	Safe zone: Ohlson-score $<$ 0.38	X^5	NI/TA
	Distress zone: Ohlson-score $>$ 0.38	X^6	FFO/TL
		X	1, if TL > TA, 0 else
		Y	1, if net loss t & t-1, 0 else
		X^9	$NI_t - NI_{t-1}/\lvert NI_t\rvert - \lvert NI_{t-1}\rvert$
Altman (1983)	Altman score $= 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$	X_1	WC/TA
		X_2	RE/TA
	Safe zone: Z'' > 2.60	X_3	EBIT/TA
	Grey zone: 1.10 < Z'' < 2.60	X_4	BVE/BVTL
	Distress zone: Z'' < 1.10		
Zmijewski (1984)	Zmijewski score = $- 4.3 - 4.5X_a + 5.7X_b + 0.004X_c$	X_a	NI/TA
		X_b	TL/TA
	Safe zone: Zmijewski score < 0.50	X_c	CA/CL
	Distress zone: Zmijewski score > 0.50		

9.4 Summary statistics of treatment and control units

Table 9.10 is a representation of summary statistics on the treatment (crowd borrowers) and control units in our data sample before and after matching. The table shows how the mean and median values of assets and liabilities are more equal after the matching. But on the other side its seems like the age of control units have become a bit higher than at the starting point.

Table 9.10: *Summary statistics for treatment and control units before and after matching*

Treatment and control group statistics		**Before matching**		**After matching**	
		Treatment	*Control*	*Treatment*	*Control*
Nr. of observations		88	54657	67	67
Age	*Mean*	8.86	7.04	8.64	10.37
	Median	7	4	6	7
Assets (2017)	*Mean*	15299.02	62164.38	11680.18	11766.52
	Median	5853	2457	4967	4462
Liabilitites (2017)	*Mean*	10889.22	29792.54	9740.46	10127.88
	Median	4533.5	965	4408	3104

9.5 Financial ratios used in the bankruptcy prediction models

Table 9.11: *Financial ratios and their abbreviations presented in each bankruptcy prediction model*

Ratio	Abbreviation	Ohlson (1980)	Altman (1983)	Zmijewski (1984)
$\frac{\text{Net income}}{\text{Total assets}}$	NI/TA	X		X
$\frac{\text{Total loabilities}}{\text{Total assets}}$	TL/TA	X		X
$\frac{\text{Current assets}}{\text{Current liabilities}}$	CA/CL			X
$\frac{\text{Working capital}}{\text{Total assets}}$	WC/TA	X	X	
$\frac{\text{Retained earnings}}{\text{Total assets}}$	RE/TA		X	
$\frac{\text{EBIT}}{\text{Total assets}}$	EBIT/TA		X	
$\frac{\text{BV of equity}}{\text{BV of total liabilities}}$	BVE/BVTL		X	
$\frac{\text{Total assets}}{\text{GNP}}$	TA/GNP	X		
$\frac{\text{Current liabilities}}{\text{Current assets}}$	CL/CA	X		
$\frac{\text{Funds from operations}}{\text{Total liabilities}}$	FFO/TL	X		
$\frac{\text{Net income}_t - \text{Net income}_{t-1}}{\lvert\text{Net income}_t\rvert + \lvert\text{Net income}_{t-1}\rvert}$	NI_t-NI_{t-1}/|NI_t|-|NI_{t-1}|	X		

9.6 Borrowers distributed into Standard & Poor's bond rating based on Altman-scores

Table 9.12*: A detailed presentation of how different crowd borrowers and regular borrowers are distributed in different Standard & Poor's bond ratings based on Altman – scores. As well there is a detailed presentation of how crowd borrowers across platforms are distributed in the bond ratings*

				Crowd borrowers		Monner		FundingPartner		Kameo		Regular borrowers		
	Rating	Threshold	Default probability (%)	N	%	N	%	N	%	N	%	N	%	Average values
Safe	AAA	> 8.15	0 - 0.25	14	20,9 %	6	20,0 %	5	23,8 %	3	18,8 %	24	35,8 %	23,9 %
	AA+	8.15	0.25 - 0.37	3	4,5 %	1	3,3 %	1	4,8 %	1	6,3 %	1	1,5 %	4,1 %
	AA	7.60	0.37 - 0.43	1	1,5 %	0	0,0 %	0	0,0 %	1	6,3 %	0	0,0 %	1,5 %
	AA-	7.30	0.43 - 0.50	1	1,5 %	1	3,3 %	0	0,0 %	0	0,0 %	0	0,0 %	1,0 %
	A+	7.00	0.50 - 0.62	3	4,5 %	2	6,7 %	0	0,0 %	1	6,3 %	0	0,0 %	3,5 %
	A	6.85	0.62 - 0.79	0	0,0 %	0	0,0 %	0	0,0 %	0	0,0 %	1	1,5 %	0,3 %
	A-	6.65	0.79 - 1.00	1	1,5 %	1	3,3 %	1	4,8 %	0	0,0 %	1	1,5 %	2,2 %
	BBB+	6.40	1.00 - 1.19	2	3,0 %	0	0,0 %	0	0,0 %	1	6,3 %	0	0,0 %	1,8 %
	BBB	6.25	1.19 - 1.73	0	0,0 %	0	0,0 %	0	0,0 %	0	0,0 %	3	4,5 %	0,9 %
	Total			**25**	**37,3 %**	**11**	**36,7 %**	**7**	**33,3 %**	**7**	**43,8 %**	**30**	**44,8 %**	**39,2 %**
Grey	BBB-	5.85	1.73 - 2.00	1	1,5 %	1	3,3 %	0	0,0 %	0	0,0 %	1	1,5 %	1,3 %
	BB+	5.65	2.00 - 2.90	2	3,0 %	1	3,3 %	1	4,8 %	0	0,0 %	4	6,0 %	3,4 %
	BB	5.25	2.90 - 3.56	3	4,5 %	1	3,3 %	1	4,8 %	1	6,3 %	1	1,5 %	4,1 %
	BB-	4.95	3.56 - 4.00	0	0,0 %	0	0,0 %	0	0,0 %	0	0,0 %	0	0,0 %	0,0 %
	B+	4.75	4.00 - 5.48	2	3,0 %	0	0,0 %	2	9,5 %	0	0,0 %	1	1,5 %	2,8 %
	Total			**8**	**11,9 %**	**3**	**10,0 %**	**4**	**19,0 %**	**1**	**6,3 %**	**7**	**10,4 %**	**11,5 %**
Distress	B	4.50	5.48 - 7.59	3	4,5 %	1	3,3 %	0	0,0 %	2	12,5 %	5	7,5 %	5,6 %
	B-	4.15	7.59 - 10.00	1	1,5 %	0	0,0 %	1	4,8 %	0	0,0 %	6	9,0 %	3,0 %
	CCC+	3.75	10.00 - 20.96	5	7,5 %	2	6,7 %	2	9,5 %	1	6,3 %	5	7,5 %	7,5 %
	CCC	3.20	20.96 - 34.97	5	7,5 %	3	10,0 %	1	4,8 %	1	6,3 %	4	6,0 %	6,9 %
	CCC-	2.50	34.97 - 50.00	7	10,4 %	3	10,0 %	2	9,5 %	2	12,5 %	2	3,0 %	9,1 %
	D	< 1.75	> 50.00	13	19,4 %	7	23,3 %	4	19,0 %	2	12,5 %	8	11,9 %	17,2 %
	Total			**34**	**50,7 %**	**16**	**53,3 %**	**10**	**47,6 %**	**8**	**50,0 %**	**30**	**44,8 %**	**49,3 %**
	TOTAL			**67**	**100,0 %**	**30**	**100,0 %**	**21**	**100,0 %**	**16**	**100,0 %**	**67**	**100,0 %**	**100,0 %**

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