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A Cross-Border Comparison of Crowdlending in Norway and Sweden

Regulations' impact on credit quality and credit risk premiums

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Abstract

Crowdfunding has experienced enormous growth in recent years, and the form of crowdfunding that has grown most is crowdlending. A key reason for this growth is that crowdlending has given small and medium enterprises easier access to capital. There are currently no common regulations for crowdlending in Europe, and the regulations for crowdlending in Norway and Sweden are different. However, the European Union has recently passed a common regulation which will make regulations more equal between the countries in the future.

This thesis investigates whether there are differences in credit quality among companies that seek financing through crowdlending in Norway and Sweden. It also investigates if there are differences in credit risk premiums cross-border. The results from these analyses could provide insight into what will happen after the implementation of the common EU regulations.

To analyze this, we construct a dataset containing information about companies that have received funding through Norwegian and Swedish crowdlending platforms from 2017 through 2020. A range of OLS regression models are estimated to determine the relationship between credit quality and country of issuance and between credit risk premium and country of issuance. The empirical results demonstrate that the credit quality of companies receiving funding through Swedish crowdlending platforms has been significantly higher than for their Norwegian counterparts. They further show that credit risk premiums for loans issued through Swedish crowdlending platforms have been significantly higher than for loans issued through Norwegian platforms.

We argue that the main reason explaining the relatively poorer credit quality in Norway than in Sweden is the current regulations. Specifically, we point to the peculiar Norwegian investment limit of NOK 1 million per year. Further, we argue that the relatively lower credit risk premiums in Norway constitutes an anomaly due to the same reason.

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The purpose of this thesis has been to improve the knowledge about crowdlending as we believe it will be an important asset class going forward. It has been truly rewarding working with the thesis. We hope the readers will enjoy reading it as much as we enjoyed writing it.

Norwegian School of Economics

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1. Introduction

Crowdfunding is a form of financing that has experienced enormous growth in the last decade. In Europe, there was a compounded annual growth rate of 44% between 2015 and 2018 (Ziegler et al., 2020). Norway and Sweden have experienced even higher growth, with compounded annual growth rates in the same period of 200% and 157%, respectively (Ziegler et al., 2019). One of the reasons for this growth is that crowdfunding has given small and medium enterprises (SMEs) easier access to capital, which is one of the biggest challenges for these companies (European Union, 2020). This has been a problem for SMEs even in countries with stable access to bank finance throughout the financial crisis (European Union, 2020). Another potential reason for the growth may be the attractive return on capital for investors and the possibility to diversify portfolios with another asset class.

The great emergence and importance of crowdfunding has also led to a debate about how to regulate the industry (European Crowdfunding Network, 2017). Regulation of crowdfunding entails which laws and rules that apply to the project owner receiving funding, the investors funding the project, and the crowdfunding platform acting as an intermediary. The regulations have been different among the various countries in Europe, where some countries have implemented a special Act for crowdfunding, while other countries have not (European Crowdfunding Network, 2017).

As there have been no common regulations for crowdfunding in Europe, Norway and Sweden have different regulations. Industry players have encountered challenges around stricter restrictions in Norway than in Sweden (Kameo, 2019). For further growth in the crowdfunding industry in Europe, the European Union wants to facilitate cross-border investing and the provision of crowdfunding services (European Union, 2020). As a result, the European Union created a common set of rules for all member states that will enter into force in November 2021 (European Union, 2020). These regulations are much more similar to the current Swedish regulations than the Norwegian regulations. The Norwegian regulations will thus become more similar to the current Swedish regulations.

The fact that Norwegian regulations will converge towards Swedish regulations makes it interesting to assess differences between the markets, as this could provide insights on what to expect in Norway. Among the different segments within crowdfunding, the lending-based segment has the highest market volume and the highest growth in Norway and Sweden, and in Europe in general (Statens Offentliga Utredningar, 2018). This motivates us to analyze differences in credit quality and credit risk premiums for companies receiving funding through crowdlending between Norway and Sweden.

1.1 Research questions

If differences in crowdlending regulations influence the selection of companies receiving funding through crowdlending, then this should also be evident in the credit quality of comparable companies cross-border. Moreover, if differences in credit quality are evident, this further suggests that convergence of regulations cross-border could imply convergence in credit quality. This motivates the first research question of this thesis:

"Are there any differences in credit quality between Norwegian and Swedish companies receiving funding through crowdlending?"

The credit quality of a company receiving funding through crowdlending impacts the risk of investing in a loan issued to that company. Thus, standard economic theory would suggest that differences in credit quality should affect the credit risk premium on that loan. This motivates the second research question of this thesis:

"Are there any differences in credit risk premiums on loans issued to comparable Norwegian and Swedish companies through crowdlending?"

1.2 Delimitations

In order to answer the research questions as precisely as possible, we will make the following delimitations. First and foremost, we will analyze loans issued to companies, and will disregard loans issued to individuals. Further, we will analyze loans issued to companies in Norway and Sweden and disregard loans issued to companies in other countries. Lastly, the companies will be analyzed at the time when they received funding through crowdlending for the first time. This is because when a company applies for a loan for the first time, the investors must rely solely on financial statements. The next time the company applies for a loan, investors will have additional information about their repayment of the first loan.

1.3 Outline

The thesis is structured in the following way: Chapter 2 provides a review of relevant literature as well as a more detailed background for the thesis. Chapter 3 describes the chosen methodology used for empirical analysis. Chapter 4 describes the data collection process and the data pre-processing, in addition to descriptive statistics about the dataset. Chapter 5 presents the empirical results of the analysis. Chapter 6 includes a discussion of the empirical results in light of the research questions. Chapter 7 summarizes the thesis and concludes on the research questions. Chapter 8 addresses any possible limitations with the thesis.

2. Literature Review and Background

Crowdfunding has experienced tremendous growth over the last decade, and this has led to more reports and research on the subject. There is still little research on crowdfunding compared to other types of financing, but in this chapter, we will present the existing research. Firstly, we will present previous research on crowdfunding. Secondly, we will address the different types of crowdfunding. Thirdly, we will present research on crowdlending, which is the focus of this thesis. Finally, we will elaborate on the Norwegian and Swedish crowdlending markets, including platforms, market growth, and regulations.

2.1 Crowdfunding

One of the earliest known crowdfunding events happened in 1885, when Joseph Pulitzer, a newspaper publisher, raised $102,000 from the New York citizens to the pedestal of the Statue of Liberty (Gierczak et al., 2015). Although financing projects with the help of the crowd is not a new concept, there has been increased attention and growth of crowdfunding the last two decades. One of the main reasons for this is that it has become much easier to reach the crowd through the internet. As crowdfunding is an emerging concept that constantly evolves, a complete definition without limitations is difficult to find (Mollick and Kuppuswamy, 2014).

Gierczak et al. (2015) describe crowdfunding as a source of financing where: *"A large amount of money can be raised by accumulating small contributions from a large group of backers."* This usually happens via crowdfunding platforms on the internet, which means that financial intermediaries such as banks are avoided (Mollick, 2014). Belleflamme et al. (2010) further state that the objective of crowdfunding is to collect money for investments and provide entrepreneurs with an alternative way of financing.

2.1.1 Types of crowdfunding

Crowdfunding is often divided into four different categories: donation-based, reward-based, equity-based, and lending-based crowdfunding (Kuti and Madarász, 2014; Mollick, 2014). For all types, the crowd invests a monetary amount in a cause, a project, or a company. The main difference between them is how the investors are repaid. In donation- and reward-based crowdfunding, investors do not receive any monetary returns. However, investors in reward-based crowdfunding receive a repayment in the form of a product or a service (Kuti and Madarász, 2014; Mollick, 2014). In equity-based crowdfunding, investors receive a share of the equity of the company receiving funding (Kuti and Madarász, 2014; Mollick, 2014). In lending-based crowdfunding, the investors usually receive a fixed interest during the loan period, and the principal repaid at maturity (Kuti and Madarász, 2014; Mollick, 2014).

2.2 Crowdlending

Lending-based crowdfunding, referred to as crowdlending, is usually divided into two types: Business and consumer loans (Baeck et al., 2014). Business loans are mainly given to small and medium enterprises, i.e., SMEs (Dietrich et al., 2019).

Baeck et al. (2014) conducted a survey on important factors for why borrowers and lenders use crowdlending platforms. Their findings provide information on why there is supply and demand for crowdlending. They found that the three most important factors for why borrowers seek financing through crowdlending are because it is easier to get funding than through traditional channels such as banks, how quick they can receive financing and the ease of use of crowdlending platforms. For the lenders, the three most important things are to make a financial return, to diversify their portfolio, and to support an alternative to the big banks (Baeck et al., 2014).

2.3 Crowdlending in Norway and Sweden

Crowdlending platforms were established later in Norway and Sweden than in many other countries. The first Swedish crowdlending platform offering business loans was established in 2013, and this platform is called Toborrow (Statens Offentliga Utredningar, 2018). Other active Swedish platforms offering business loans are Kameo (2014), Tessin (2014), Savelend (2014), and Trine (2015). Norway established its first platform later than Sweden. Kameo arranged the first crowdlending business loan in Norway in 2017 (Weldeghebriel, 2018). One of the reasons for the late start is the strict and unclear regulations for operating a crowdlending platform in Norway (Norges Offentlige Utredninger, 2018). In addition to Kameo, Monner (2018) and FundingPartner (2018) constitute the market for business loans in Norway. There are only a few reports about crowdlending statistics for Norway and Sweden. Cambridge Center for Alternative Finance published an international report, and this report provides market data for 2016 and 2017. In addition, Shneor (2021) has collected data on the Norwegian market on behalf of the Norwegian Crowdfunding Association. In 2016, the total market volume of business loans[1] in Sweden was $27.2 million, and in 2017 the volume had grown to $58.5 million, which implies an annual growth of 115% (Ziegler et al., 2019). No business loans were given in Norway in 2016, but the total volume in 2017 was $2.9 million (Ziegler et al., 2019). According to Shneor (2021), the total market volume in Norway was $30.8 million in 2019, and $52.9 million in 2020. The annual growth rate in Norway from 2019 to 2020 is 71%. Data from these two reports indicate that crowdlending in Norway and Sweden are experiencing a tremendous growth, and especially in the business loans segment.

2.3.1 Regulations

2.3.1.1 Current regulations

As crowdlending is still a relatively new form of financing, there are still discussions about regulations for crowdlending platforms. Since there are no common set of rules across countries, the Norwegian market is subject to Finanstilsynet's (Norwegian Financial Authority) regulations, and the Swedish market is subject to Finansinspektionen's (Swedish Financial Authority) regulations. The regulations are currently very different between Norway and Sweden, which affect the development of crowdlending within the countries.

In Norway, there is no separate law or licensing for crowdlending, and the platforms are therefore subject to The Financial Supervision Act. This implies, among other things, that the platforms cannot offer loan pools, which is a collection of several loans (Finanstilsynet, 2018). Further, any investor, either individual or institutional, cannot invest more than NOK 1 million per year (Finanstilsynet, 2019). Additionally, Norwegian crowdlending platforms are required to be independent of both the borrower and the lender (Finanstilsynet, 2017; Næsse, 2019). This means that the crowdlending platforms cannot facilitate forced collection of the loan principal in the event of default. Instead, the loan agreements typically include a clause that regulates the potential forced collection by the use of a debt collection partner such as Lindorff Finans (Berg, 2019). A review of Norwegian crowdlending platforms

[1] Business loans are loans given to businesses, including real estate.

shows that their debt collection partners typically charge between 10% and 20% of the collected amount (Appendix A 1).

There is no separate law for crowdlending in Sweden either. Crowdlending is therefore subject to The Banking and Finance Business Act (Statens Offentliga Utredningar, 2018). However, this law has different implications on crowdlending than in Norway. In Sweden, loan pools are not prohibited, and there is no investment limit of NOK 1 million. This means that Swedish platforms may issue loans that are guaranteed to be fully subscribed by either professional investors or financial institutions. Further, Swedish platforms are allowed to facilitate the forced collection of principal in the event of default. Thus, there is no legal requirement for platforms to use debt collection partners.

In summary, the regulations in Norway and Sweden are different, and the biggest differences are specified above. Hereunder are the limitations regarding investment amount, loan pools, and debt collection partner requirements. The more restrictive regulations in Norway have huge implications and make the Norwegian crowdlending market unattractive for both existing and new players, according to the Norwegian Crowdfunding Association (Norsk Crowdfunding Forening, 2019).

2.3.1.2 New European Union regulative: Common regulations

In order to create a uniform set of rules for crowdlending platforms, the European Union passed a common regulation for all member states in October 2020, which will apply from November 2021 (European Union, 2020). European Union (2021) defines a regulation as "a binding legislative act", which implies that the regulation will apply in the member states without having to be adopted by each individual country. The regulation is currently being considered by the EFTA states[2] with the aim of implementing it in the EEA Agreement[3]. This will also make the regulation applicable in Norway (Regjeringen, 2021).

The EU regulation will have many implications for crowdlending in Europe (European Union, 2020). The definition of crowdlending platforms will change in the legislation of the

[2] European Free Trade Association are states that do not belong to the European Union (EU) but have many of the same agreements and rules. Norway is one of the EFTA states.

[3] European Economic Area (EEA) Agreement is a trade agreement between the EFTA states and the EU states.

European countries. This legislation will only apply for business loans up to €5 million[4] per year for each project owner without the obligation of drawing up a prospectus. Further, it will be created a separate license to operate crowdlending platforms. For this new licensing, a common set of rules will be made for all EU and EEA countries. The goal is that cross-border crowdlending will be easier, more accessible, and cheaper (European Union, 2020). This will enable investors to have a more diversified portfolio, and project owners will be more likely to get fully subscribed loans.

Further, a distinction will be made between sophisticated and non-sophisticated investors. One of the purposes of this distinction is to ensure adequate investor protection. The crowdlending platforms are subject to several measures to address this issue. They will have a responsibility to ensure that non-sophisticated investors acknowledge the risk associated with the investment. In addition, the non-sophisticated investors will be allowed to invest a maximum amount in each project without further safeguards. The sophisticated, professional investors will, on the other hand, not be subject to any maximum amount limit. This will most likely also contribute to higher subscription rates on the loans.

The EU regulation will cause the Norwegian regulations to converge towards the current Swedish regulations. The peculiar investment limit for Norwegian investors of a maximum of NOK 1 million per year will disappear, and the new practice will consequently be similar to the current Swedish regulations. Removing this rule in Norway may greatly impact the further development of crowdlending, as the restriction currently makes it less interesting for professional investors and financial institutions to invest in crowdlending.

The new EU regulation has been well received by the crowdlending community in Norway. The previous Chairman of the Norwegian Crowdfunding Association and CEO of FundingPartner, Geir Atle Bore, has commented on the new regulation. He believes it will be a gamechanger for Norwegian crowdlending and lead to both increased consumer protection and growth (Nilssen, 2020). According to Deloitte, the new regulation will lead to big changes for the crowdlending market in Norway (Deloitte Advokatfirma, 2021). Deloitte believes it will most likely lead to increased demand for crowdlending services.

[4] Equivalent to NOK 51 million (27.03.21).

2.3.1.3 Perceived adequacy of current regulations and market volumes

Analysis from Ziegler et al. (2020, p. 105) shows the relationship between perceived regulatory adequacy and market volume per capita in European countries. It indicates a strong positive relationship between the share of platforms indicating adequate regulation and the alternative finance volume per capita for the respective countries. Figure 1 shows that the majority of platforms operating in Norway perceive the regulation as inadequate, as opposed to in Sweden. Further, it shows that the volume per capita is considerably lower in Norway than in Sweden.

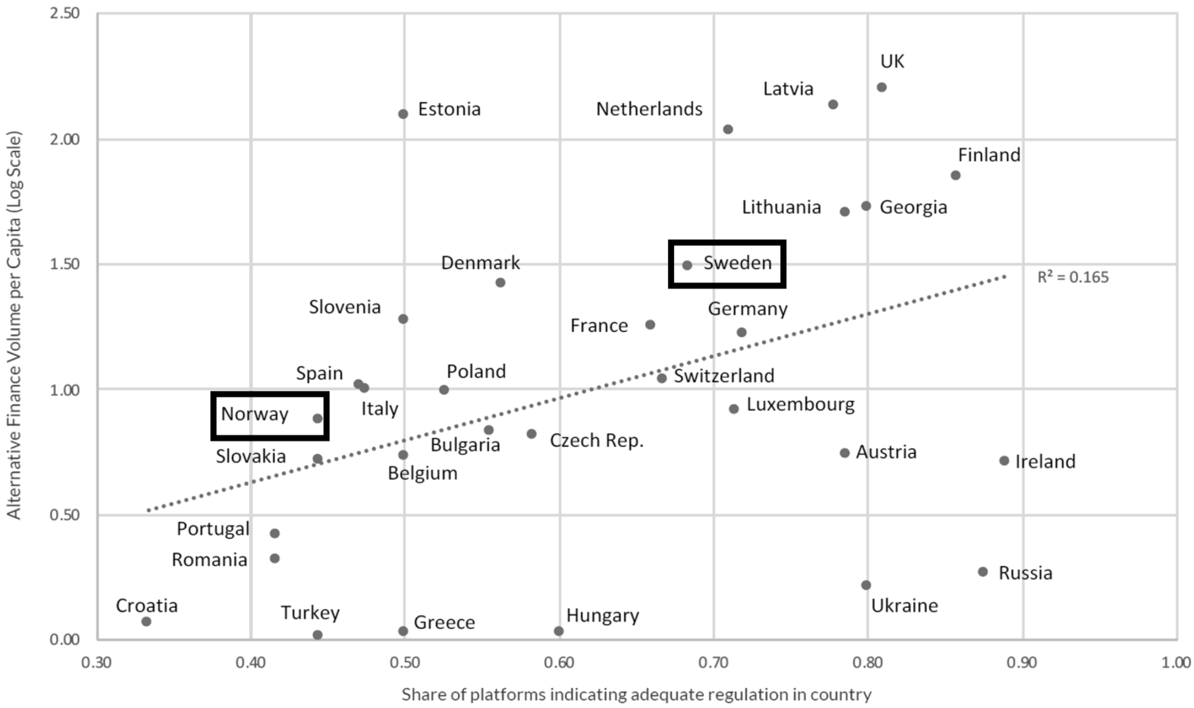

Figure 1: Regulation adequacy and alternative finance volume

3. Methodology

In this chapter we will elaborate on the methodologies we will be using in the analysis. Firstly, the motivation for applying matching in the pre-processing of data, and the choice of method are described. Secondly, bankruptcy prediction models which will serve as proxies for credit quality will be described. Thirdly, winsorization as a tool for handling extreme outliers will be described. Lastly, we will elaborate on the chosen estimators for statistical inference.

3.1 Matching

In experimental research, it is possible to determine valid causal inference due to three important features related to the data generation process: (1) Random selection, (2) random assignment, and (3) large sample size (Ho et al., 2007). These features, commonly associated with Random Control Trials (RCT), are considered to be the "gold standard" for determining the causal effects of medical interventions (Wooldridge, 2016). In our case, however, it is neither practically feasible nor appropriate to conduct either scientific experiments or intervention studies. Thus, our study relies on observational data about actual loans and borrowers in Norway and Sweden. By using observational data, a key issue regarding the data generation process is raised: The mechanism for assigning treatment is not under the control of the researchers. This implies that the assignment mechanism is not random, which is a potential source of bias. Furthermore, using observational data opens up for bias from model dependence (King and Zeng, 2007).

In order to address these issues, Iacus et al. (2012) suggest using a data pre-processing technique called matching. By using well-matched samples from the groups of treated and untreated it is possible to reduce both model dependence and statistical bias. Several different matching techniques have been used extensively across research disciplines such as economics, epidemiology, medicine and political science. Stuart (2010) presents a review of their prevalence and applications. The most prominent technique by far is the Propensity Score Matching technique (from here on "PSM"), which was first defined by Rosenbaum and Rubin in 1983. However, recently the PSM technique has been found to be dominated by other techniques such as Coarsened Exact Matching (from here on "CEM"). A study conducted by King and Nielsen (2019) shows that PSM actually leads to increased imbalance, decreased efficiency, increased model dependence, and increased statistical bias. The same study determines that CEM is dominant relative to PSM. We therefore choose to apply the CEM technique in this thesis.

3.1.1 Coarsened exact matching

In this subchapter the CEM matching technique will be described. The CEM technique was first presented in a paper by Iacus, King and Porro (2008). Here, the authors introduce a new class of matching techniques in addition to Equal Percent Bias Reducing class (from here on "EPBR") in which PSM belongs. The new class is named Monotonic Imbalance Bounding. CEM belongs to the new class, and in a subsequent paper by Iacus, King and Porro (2012), the benefits of CEM are substantiated further. Compared to PSM and other EPBR techniques, CEM guarantees that the imbalance between matched samples is reduced ex ante the researcher's choice. Further, CEM does not require additional assumptions to be made, other than the standard ignorability assumption as below.

Conditional on X the treatment variable is independent of potential outcomes:

$$T_i \perp\!\!\!\perp \{Y_i(0), Y_i(1)\} \mid X$$

The goal of CEM is to pre-process data by coarsening observations of each variable into exact or broader groups. Continuous variables can be grouped in intervals, while categorical variables can be grouped in larger categories. When CEM has been successfully implemented the data is ready for further analysis by standard econometric techniques. Implementation of CEM can be divided into three distinct steps (Iacus et al., 2012):

1. **Coarsening:** An informed choice on which variables to include in the matching, and how they should be coarsened must be made. This includes first to determine if a variable should be matched exactly or coarsened. If the variable should be coarsened, the researcher must determine the size of the bin interval. This step is the most important for implementing CEM as it determines the boundaries for both model dependence and estimation error.
2. **Implementation:** The previously determined matching criterion is implemented and the observations are sorted into strata. This step is typically conducted in a statistical software such as R or Stata.

3. **Analysis:** Only strata containing observations from the groups of both treated and untreated are retained for further analysis. If there are stratum containing uneven numbers of control observations compared to treated observations, then CEM requires that weighting must be included.

3.1.1.1 Coarsening

Literature does not provide a clear answer as to which variables should be included in the coarsening. However, Iacus et al. (2012) state that variables deemed as relevant by the researchers, based on their existing in-depth knowledge on the subject should be used. Another obvious boundary in observational studies is to use observed variables. Further, Ho et al. (2007) state that variables that could even slightly be affected by the treatment variable should never be controlled for, as this would prevent causal inference due to bias. The goal of our analysis is to pinpoint differences in credit quality and credit risk premiums across the Norwegian and the Swedish crowdlending markets due to differences in regulatory climate. Thus, any variables that might be regarded as a consequence of why the company has taken a loan through a Swedish crowdlending platform should not be controlled for.

Further, the more coarsened each variable is, or in other words, the larger each "bin interval" is, the more of both model dependence and estimation error is allowed (Iacus et al., 2012). This is because fewer observations are dropped leaving a higher number of matches. Conversely, the less coarsened each variable is, or in other words, the smaller each "bin interval" is, the less model dependence and estimation error is allowed. This is because more observations are dropped, due to fewer matches. Thus, the decision of how coarsened each variable should be includes a trade-off that the researcher must take into account. The researcher can use small bin intervals and discard a lot of data or use broad bin intervals and retain more data.

The variables and their corresponding bin size used in the analysis are the following:

Size: Companies of different sizes may vary greatly on a wide set of dimensions, such as capital structure, governance structure, sources of financing and more. Thus, this variable is deemed relevant to include. In our data, each company's level of total assets on the balance sheet is used as a proxy for its size. Alternative measures could be the number of employees or annual turnover. As the size of companies engaging in crowdlending in Norway and

Sweden usually range from total capital of NOK 0,- to NOK 250 000 000,- we find it purposeful to coarsen this variable into four different bin intervals as presented in Table 1.

BIN	**TOTAL CAPITAL**
Negative	< NOK 0
Small firms	NOK 0 to NOK 20 000 000
Medium firms	NOK 20 000 001 to NOK 100 000 000
Large firms	> NOK 100 000 000

Table 1: Bin intervals for total capital

Year: In order to avoid bias from time variant economic effects we include the year of reporting for each company's financial statements. This way we avoid comparing a company that took a loan in 2016 with a company that took a loan in 2019. As year is an integer variable, we choose to employ exact matching.

Industry: Companies may vary greatly across industries on many different dimensions, such as capital structure, governance structure, sources of financing and more. Thus, this variable is deemed relevant to include. In our data, we have registered each company's industry based on the industry it is assigned to on the crowdlending platforms. As industry is a categorical variable, we choose to employ exact matching.

Age: Age of a company influences the company in many ways. Older companies are more likely to have an established business model, and are often perceived as less risky. Further, older companies have a longer accounting history making it easier to assess their performance. Robb (2002) classifies companies by age in the following intervals: Young firms less than 5 years, middle aged firms, 5-24 years old, old firms 25 years and older. We choose to use the same classification as Robb, as it fits well with our knowledge of companies engaging in crowdlending activities. Table 2 presents an overview of the coarsening.

BIN	**COMPANY AGE**
Young firm	0 to 4 years
Middle aged firms	5 to 24 years
Mature firms	> 24 years

Table 2: Bin intervals for age

Table 3 presents an overview of the included variables:

VARIABLE	COARSENING
Size	Intervals
Reporting year	Exact
Industry	Exact
Age	Intervals

Table 3: Overview of matching variables

3.1.1.2 Imbalance measurements

The purpose of pre-processing data with CEM is to reduce imbalance between the observations of the treated and control units, thus reducing both model dependence and estimation error. In order to determine the scope of improvement, it is useful to measure imbalance between the samples before and after matching. As our samples include data on several variables, such a metric should encompass the distance between the multivariate empirical distributions of pretreatment covariates. For this exact purpose, Iacus et al. (2011) propose to use the L_1 imbalance measurement which is presented below:

$$\mathcal{L}_1(f,g;H) = \frac{1}{2}_{\ell_1 \dots \ell_k \in H(X)} \sum |f_{\ell_1 \dots \ell_k} - g_{\ell_1 \dots \ell_k}|$$

The variables *f* and *g* denote the respective relative empirical frequency distribution for the treated and control units. Further, the term $f_{\ell_1 \dots \ell_k}$ denotes the relative frequency for observations belonging to the cell with coordinates $\ell_1 \dots \ell_k$ of the multivariate cross-tabulation. The term $g_{\ell_1 \dots \ell_k}$ denotes the corresponding relative frequency for the cell with coordinates $\ell_1 \dots \ell_k$. Lastly, the *H* term denotes a set of bins, and is included to underscore the importance of using the same set of bins when comparing imbalance across matching methods.

The L_1 measurement proposed by Iacus et al. (2011) has several advantages compared to other imbalance measurements. Firstly, it encompasses the distance between the multivariate empirical distributions of pretreatment covariates. Other commonly used measurements do not encompass this, but typically rather only measure the average of differences in means across the matched treatment and control samples. Secondly, the L_1 measurement is easy to understand and has an intuitive interpretation: For any given set of bins represented by *H* the

L_1 measurement is equal to 0 if the multivariate empirical distributions exactly coincide, or 1 if they are completely separated. Thus, any decrease in the L_1 statistic after matching equals reduced imbalance between the samples of observations of the treated and control units.

3.1.1.3 K-to-K matching

According to Ho et al. (2007), if the matching method used produces matches with an equal number of treated and control units in each stratum, any analysis method that would have been used without matching, such as for example OLS regression, can be applied on the matched dataset only with lower model dependence after matching. This is also known as K-to-K matching. Thus, K-to-K matching eases both analysis and interpretation of the results after matching. However, if the used matching method allows for K-to-J matching, effectively allowing different numbers of treated and control units in each stratum, one must adjust the analysis method. Iacus et al. (2012) describe one such method, where the researcher must weigh or adjust for stratum sizes in order to determine the causal effect of interest. The advantage of allowing for K-to-J matching is that one does not have to remove as much data as when it is only allowed for K-to-K matching. In our view, the advantages of K-to-K matching are favorable in comparison to the alternative of using K-to-J matching. This is in particular true because we find that K-to-K matching is feasible with the amount of data we possess. We therefore restrict the CEM algorithm to K-to-K matching.

The method we use to implement K-to-K matching is described by Iacus et al. (2009), and is based on random matching inside each stratum. To exemplify; a stratum of one treated unit matched in a stratum with five control units would be reduced to a matched pair of the same treated unit and a randomly chosen unit among the other five. According to Iacus et al. (2009) this method of randomly selecting the matching within each stratum could further reduce bias.

3.2 Choice of method for analysis of credit quality

It is in our interest to find a quantitative measure for credit quality to be able to answer the first research question. The credit quality of a company is related to what type of credit rating the company has. Credit rating is determined based on how likely it is that the borrower will be able to repay the loan, i.e., the probability that the company will go bankrupt (Kagan, 2021). Among the alternatives for this are structural credit risk models and bankruptcy prediction models.

One method for determining credit quality is structural credit risk models, such as Robert C. Merton's model from 1974 (Sundaresan, 2009, p. 210). This model gives a quantitative assessment of credit quality by calculating the probability of default and the loss given default. One of the required variables for using this model is the standard deviation of stock returns, i.e., stock volatility. Since this is not possible to estimate for private crowdlending companies, Merton's model is not suitable as a proxy for credit quality in this analysis.

Another method for analyzing credit quality is bankruptcy prediction models, such as the Altman Z-score model from 1968 (Altman, 1968). This model estimates a score for a company based on ratios from the financial statements. The score determines whether the company is likely to be bankrupt or not within one year. Since there is no publicly available information about the credit rating of companies receiving funding through crowdlending in Norway and Sweden, bankruptcy prediction models constitute the most suitable way to address credit quality.

3.3 Bankruptcy prediction models

In this subchapter we will elaborate on the development within bankruptcy prediction models. In addition, the fundamental differences between different approaches to prediction bankruptcy will be explained in detail. Firstly, we will describe the general types of bankruptcy prediction models. Thereafter, the two chosen models will be described and the reasoning for the choice will be motivated.

3.3.1 Types of bankruptcy prediction models

If a company becomes insolvent, there will be negative consequences for most of the stakeholders in the company, such as investors, employees, customers, and suppliers (Jackson and Wood, 2013). This implies that many players have a great interest in knowing whether a company is healthy or not. Bankruptcy prediction models can provide insight on the financial health of companies. As a result of many defaults and bankruptcies, as well as developments in requirements for banks, bankruptcy prediction models have been a frequently researched topic within corporate finance the last decades (Altman and Hotchkiss, 2006, p. 233).

Many bankruptcy prediction models have been developed in the last decades, and various classical statistical methods have been used (Balcaen and Ooghe, 2006). Until the 1960's, univariate analysis was the dominant method (Bellovary et al., 2007). In univariate analysis, the predictive ability is measured for one financial ratio at a time (Beaver, 1966). Since the 1960's, multivariate analysis has been more frequently used (Bellovary et al., 2007). It differs from a univariate analysis in that it looks at several different ratios at a time (Beaver, 1966). Within multivariate analysis, the most common statistical techniques for bankruptcy prediction models are discriminant analysis, logit analysis, probit analysis and neural networks (Bellovary et al., 2007).

Research shows that none of the multivariate methodologies have a clearly higher predictive power than the other. Laitinen and Kankaanpää (1999) tested the accuracy of several methodologies used in bankruptcy prediction models. They found that neither logit analysis, neural networks, or other methodologies are significantly better than linear discriminant analysis. Another paper from Azir and Dar (2006) substantiates this. They find that the predictive accuracy between the different methodologies is comparable.

Multivariate discriminant analysis (from here on "MDA") is a method that is easy to use, applicable and effective (Peres and Antão, 2016). None of the other methods for predicting bankruptcy are as simple to use, interpret and apply as MDA (Peres and Antão, 2016). Further, MDA is shown to provide low Type I and Type II error[5] rates, making this methodology the most reliable for predicting bankruptcies (Azir and Dar, 2006). Consequently, the MDA method is the most frequently used in bankruptcy prediction models (Jackson and Wood, 2013). Based on the high predictive accuracy and intuitive interpretation, we choose to apply MDA models in our thesis.

Altman and Hotchkiss (2006, p 239) explain how these models are derived. The first step is to classify the companies as bankrupt or non-bankrupt. After this, data from financial statements is collected. Then, a list of potential variables (i.e., financial ratios) are tested.

[5] "Type I errors are the misclassification of bankrupt firms as non-bankrupt. Type II errors are the reverse - non-bankrupt firms misclassified as bankrupt firms." (Bellovary et al., 2007).

From this test, the most suitable variables for prediction are selected. Finally, computer algorithms are utilized to determine coefficients for calculating a score for each company, and this is referred to as the Z-score. After a Z-score is calculated for each company, one can rank the companies after their Z-score. A higher Z-score means a healthier company, and vice versa. A cut-off point then divides the companies that are viable from those that are highly likely to go bankrupt. A Z-score below the cut-off point implies that the company is unhealthy. The MDA models use a similar function to calculate the Z-score (Jackson and Wood, 2013):

$$Z_i = \alpha + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_n X_{in}$$

where Z_i is the singular score of company i, α is a constant, X_{in} is the attributes (financial ratios or other variables) for company i, and β_n is the coefficient estimates for each attribute.

There are several MDA models. They have a similar form of the function for calculating Z-score, but differ in the choice of financial ratios and coefficient estimates. The variables in the function are most often ratios for profitability, liquidity, and leverage (Dambolena and Khoury, 1980).

The first MDA model for bankruptcy prediction was published by Edward I. Altman in 1968, and is known as the Altman Z-score model (Altman, 1968). This is among the most well-known models (Bellovary et al., 2007), and is also the bankruptcy prediction model that is most frequently used (Altman, 2018). The model has been shown to provide a very high predictability. It is able to predict with 95% accuracy one year prior to bankruptcy, and 72% accuracy two years prior to bankruptcy (Altman, 1968). Based on the high predictive power and reputation, we choose to apply the Altman Z-score model in this thesis.

Many of the various MDA models are derived with a dataset consisting of American companies. Richard J. Taffler derived an MDA model for European companies, and in 1983 he published a model with a dataset consisting of companies from the UK. We argue that UK companies are relatively more similar to Norwegian and Swedish companies. One of the reasons for this is that the UK was a member of the European Union until 2020, and has thus had many of the same rights and obligations as Norway and Sweden. Taffler is a well-known MDA model, which proves to have good predictive abilities decades after it was published

(Agarwal and Taffler, 2007). Consequently, we choose to apply the Taffler (1983) Z-score model in this thesis.

3.3.2 Altman's Z-score model

The Altman Z-score model is a bankruptcy prediction model first published in 1968, and the model predicts whether a company will go bankrupt within two years (Altman, 1968). This is the most used bankruptcy model (Altman, 2018), and research shows that it still provides accurate results in recent times (Sherbo and Smith, 2013). The model calculates a Z-score for a company by using financial ratios from the income statement and balance sheet. This Z-score indicates how likely it is that a company will go bankrupt within two years.

The original model from 1968 is derived using a sample of public companies, and contains five different financial ratios (Altman, 1968). Since one of these metrics includes market value of equity, this model is not applicable for private companies. In 1983, Altman published a model for private companies. The market value of equity was substituted with the book value of equity, and one financial ratio was excluded to remove a potential industry effect (Altman, 1983). Then a re-estimation was performed with a dataset of private companies to find new coefficients. Research from Altman, Iwanicz-Drozdowska, Laitinen and Suvas (2017) show that the re-estimated model performs very well in an international context. Since most of the companies funded through crowdlending are private, the 1983-model is most appropriate for this thesis. This model consists of four financial ratios for profitability, leverage, and liquidity.

The revised Altman (1983) model for private companies is the following:

$$Z_A = 3{,}25 + 6{,}56 \cdot X_1 + 3{,}26 \cdot X_2 + 6{,}72 \cdot X_3 + 1{,}05 \cdot X_4$$

where

X_1 = Working capital/Total assets (Net liquid assets)
X_2 = Retained Earnings/Total assets (Earned surplus)
X_3 = Earnings before interest and taxes/Total assets (Profitability of assets)
X_4 = Book value of equity/Book value of total liabilities (Leverage ratio)

3.3.3 Taffler's Z-score model

Taffler's Z-score model (1983) is another bankruptcy prediction model and has similar characteristics to Altman’s Z-score model. The sample used to derive this model are public industrial UK companies, but are applicable for private companies as it is only based on book values. This model also calculates a Z-score based on weighted financial ratios, and includes four ratios for profitability, working capital position, financial risk, and liquidity (Agarwal and Taffler, 2007).

Taffler (1983) found that a Z-score can be calculated using this formula:

$$Z_T = 3{,}20 + 12{,}18 \cdot X_1 + 2{,}50 \cdot X_2 - 10{,}68 \cdot X_3 + 0{,}029 \cdot X_4$$

where

X_1 = Profit before tax/Current liabilities (Profitability)
X_2 = Current assets/Total liabilities (Working capital position)
X_3 = Current liabilities/Total assets (Financial risk)
X_4 = No credit interval (Liquidity)

The fourth ratio, no credit interval, is the number of days a company would be able to finance its operations without generating any revenue (Taffler, 1983). The number of days is found by calculating quick assets/daily expenses (Kenton, 2020).

3.4 Winsorization

In a limited dataset such as ours, the average and variance of Z-scores are highly sensitive to outlier values. Therefore, we find it useful to assess the impact of outlier values by re-estimating the statistical models after adjusting for these and compare the outcomes. The technique we apply is called winsorization. According to a recent paper in the Journal of Financial Management, winsorization is the most commonly applied technique to handle outlier values in finance (Adams et al., 2019). However, the winsorization technique has been criticized for inducing some bias from changing the outlier values (Bollinger and Chandra, 2005). The potential bias introduced from winsorization is in any case less than the bias introduced from other comparable techniques, such as trimming (Bieniek, 2016). For these reasons, we choose to include results both with and without winsorization applied.

Winsorization is a technique that adjusts for outlier values by changing them to the value of a specified percentile. We choose to apply a 10% winsorization which implies that all values below the 5^{th} percentile and above the 95^{th} percentile is set equal to the value of the 5^{th} percentile and the 95^{th} percentile, respectively.

3.5 Estimator for statistical inference

Pre-processing data by applying a matching method, such as CEM, does not affect the choice of estimator for statistical inference, as long as the chosen method produces K-to-K matches (Ho et al., 2007). Thus, our choice of estimator is unaffected by the pre-processing. However, through pre-processing the data, we aim to reduce both sample imbalance and estimation error. The goal of our analysis is to assess differences in credit quality and credit risk premiums between companies receiving funding through Norwegian and Swedish crowdlending platforms. An appropriate estimator for this purpose is the Ordinary Least Squares (OLS) estimator. In the following subchapter we will first present the general statistical properties of the OLS estimator. Thereafter, the assumptions related to the estimator will be presented and discussed.

3.5.1 Ordinary Least Squares

OLS is a linear estimator that determines the coefficients in a uni- or multivariate regression by minimizing the squared sum of residuals. The estimator is in the form of the following equation:

$$Y = \beta_0 + \beta_1 \cdot X_1 + \cdots + \beta_i \cdot X_i + u$$

where β_0 represents the intercept, β_i represents the effect of the independent variable x_i on the dependent variable Y, and u represents an error term of unexplained variation.

The goal of the analysis is inter alia to infer the effect of a binary independent variable x on a continuous dependent variable Y. In cases such as these, where x_1 is a binary variable, then β_1 represents the difference in the mean value of Y across the subsamples with x = 1 and x = 0 (Wooldridge et al., 2016).

3.5.2 Assumptions

There are four critical assumptions that must hold for the OLS estimator to be unbiased (Wooldridge et al., 2016). Firstly, there must be linearity in parameters. Secondly, the sampling of observations must be random. Thirdly, there must be variation in the independent variable. Lastly, the error term u must have a zero-conditional mean.

The first assumption of linearity in parameters is trivial, as we estimate the effect of a binary independent variable x on a continuous outcome variable Y. As our study is observational, the second assumption could be more difficult to satisfy. However, by applying CEM as described in chapter 3.1.1, we have approximated random sampling. Thus, we consider the second assumption to be satisfied as well. The third assumption of variation in the independent variable is satisfied as our dataset contains observations of both Norwegian and Swedish companies. The fourth assumption about zero conditional mean in the error term must be diagnosed by assessing a plot of the residuals.

Additionally, there is a fifth and last optional assumption. It stems from the Gauss-Markov theorem and is related to *homoscedasticity* in the error term. Homoskedasticity implies that the error term u has the same variance for all values of the independent variables. This implies that the residuals should be independently and identically distributed. If this assumption holds, then the estimator is said to be the best linear unbiased estimator. However, this assumption is often violated. In such cases it is necessary to adjust the standard errors.

3.5.3 Adjusted standard errors

If heteroskedasticity is present and the residuals are correlated within groups but not between groups then it is appropriate to use clustered standard errors (Cameron and Miller, 2015). The reason for this is that the classic OLS standard errors could overstate the precision of the estimator (i.e., produce too small standard errors). In our analysis it is reasonable to assume that the residuals for observations from the same reporting year could be correlated as the company financials of that year have been exposed to the same macroeconomic factors. For this reason, we choose to report adjusted standard errors clustered on year-level.

For the sake of nuance, we will also include one other commonly used method for adjusting standard errors in Appendix A 3, namely heteroskedastic robust standard errors. There are several different methods of estimating heteroskedasticity robust standard errors. Long and Ervin (2000) conducted a study where they compared different estimators for heteroskedasticity robust standard errors which concluded that the HC3-variant should be used if the sample size is less than n = 250. Based on this, we choose to use HC3 since our sample has 108 observations.

4. Data

The analysis in this thesis is conducted on a self-constructed dataset containing information about companies that have borrowed through crowdlending platforms in Norway and Sweden. In this chapter, we will elaborate on the data we have used in our study. Firstly, the data collection process will be described in detail. Thereafter, the data cleansing and pre-processing will be described, and relevant choices will be discussed. Lastly, a set of relevant descriptive statistics will be presented, with the goal of familiarizing the readers to our data.

4.1 Data collection

To the best of our knowledge, no database containing information on crowdlending in Norway and Sweden exists. Thus, in order to conduct our analysis, we are forced to collect data and compile a dataset ourselves. The process of creating the dataset started with identifying all relevant crowdlending platforms in Norway and Sweden. Then, information about every loan issued through the said platforms was sought out and downloaded. Thereafter, a list of companies that had borrowed through these crowdlending platforms were identified. Lastly, relevant financial information about these companies was downloaded and compiled in a list. In the following chapters we will elaborate in detail on each step of the process.

4.1.1 Process and data sources

Throughout the data collection process, we have used several different sources of data. In the following we will describe the sources we have used.

Firstly, we identified all crowdlending platforms in Norway and Sweden. Norwegian platforms are easy to identify as the Norwegian Crowdfunding Association (Norsk Crowdfunding Forening, 2021) offers a comprehensive list of the crowdfunding platforms in Norway. In Sweden there is no such industry association, but the industry webpage P2PMarketData (2021) presents an overview of crowdfunding platforms in Sweden. In order to verify that no platforms are left out, we search the web using Google and Bing. In total, 14 different crowdlending platforms are identified. Out of these, eight platforms offer exclusively business loans, one offers both business and personal loans, while five offers exclusively personal loans. As the thesis focuses on loans issued to businesses and not consumers, the number of potentially relevant platforms are reduced from 14 to nine. One platform has not yet commenced operations. By removing this, the number of potentially relevant platforms are reduced from nine to eight. Lastly, two platforms focus exclusively on special purpose environmental financing in developing countries. As the focus in this thesis is to compare crowdlending in Norway and Sweden, these platforms are also removed from the list. This leaves us with a total of six relevant crowdlending platforms in Norway and Sweden.

Secondly, in order to collect information about loans issued through crowdlending, we either had to gain access to the platform or receive data sent over from the platform. We were able to register at four out of six relevant platforms, and were thus able to collect information from these. These were FundingPartner, Kameo, Monner, and Tessin. The two platforms that we did not gain access to were contacted, but did not wish to share information with us. These were Savelend and Toborrow. This is limiting the generality of our study somewhat, as it blocked us from compiling a completely exhaustive dataset. However, we are still of the opinion that the data we have collected is representative for the Norwegian and the Swedish crowdlending markets.

Thirdly, after identifying the unique companies that have borrowed through the relevant crowdlending platforms in Norway and Sweden, we collect relevant financial information about each company. This information is downloaded from Proff.no and Proff.se for the Norwegian and Swedish companies, respectively. “Proff” is a service that publishes all companies registered financial statements online in both Norway and Sweden. Thus, we are able to collect the relevant information needed for our analysis.

Lastly, we also accessed Norges Bank and Riksbanken to download information about treasury bond yields.

Table 4 presents an overview of the data sources we have used.

INFORMATION RETRIEVED	DATA SOURCE
Crowdlending platform data	Norsk Crowdfunding Forening P2PMarketData
Loan data	Crowdlending platforms
Company data	Proff.no Proff.se
Treasury bond yield data	Norges Bank Riksbanken

Table 4: Overview of data sources

4.1.2 Initial dataset

The data collection process resulted in a dataset containing loan information on 822 loans in total. Out of these, we were able to identify the legal borrowing entity for 756 loans. Among these, we identified 350 unique companies that have borrowed through crowdlending platforms at least at one point in time. Further, it was possible to collect financial information for the year T-1 for 283 out of the 350 identified companies that had issued a loan in year T. The reason for why we keep financial data for year T-1 is because this is the information that was available to investors considering investing in a loan issued in year T. The companies that did not have any public financial information were either newly established, or they had gone bankrupt and were deleted from public company registries. Consequently, the data collection process resulted in an initial dataset of 283 companies.

4.2 Pre-processing of data

In this subchapter we elaborate on how we have pre-processed the initial dataset to prepare it for analysis. We will first describe adjustments to the dataset, including additional computations. Thereafter, we describe how we apply CEM to the data.

4.2.1 Adjustments to initial dataset

Firstly, we must compute the financial ratios that are required by the bankruptcy prediction models of Altman (1983) and Taffler (1983) as described in subchapter 3.3.2 and 3.3.3, and the associated Z-scores. This is easily done in R, and we create new columns containing the Z-scores from Altman and Taffler.

Secondly, we convert the variable “Year of establishment” from a year type to age type in order to determine the age of each company. This is easily implemented by subtracting the variable “Year” which represents the fiscal year for the financial information from the variable “Year of establishment”. This way, we can use “Age” for matching and as an independent control variable in our analysis.

Thirdly, we create a separate column containing the credit risk premium for each loan. This is done by subtracting the risk-free rate from the interest rate stipulated on the loan. As a proxy for risk-free interest rate, we use the corresponding five-year treasury bond yield. Although loans have different maturity, we choose to adjust for the five-year treasury bond for all loans. This is because both the Norwegian and Swedish central banks offer treasury bonds with this maturity.

Lastly, we remove some units from the dataset as their financial data make analysis using accounting-based bankruptcy prediction models such as Altman (1983) and Taffler (1983) impossible. This is due to some of the values in the companies’ financial statements that produce infinite Z-scores. Hereunder are companies that report to have either zero total capital, zero total debt, zero current liabilities, or zero daily expenses. By removing these strange cases, the number of companies in our sample is reduced from 283 to 246, of which 131 are Norwegian and 115 are Swedish.

4.2.2 Applying CEM

In order to apply CEM we first had to create a dummy variable for observations belonging to the treatment group. Thus, we added a dummy variable with the value “1” for Swedish companies and “0” for Norwegian companies. Thereafter, we used the package “CEM” in R studio (Iacus et al., 2009) to create a sample containing the matched observations. After applying CEM with the coarsening intervals described in chapter 3.1.1.1 and K-to-K matching as described in chapter 3.1.1.3 the sample size is reduced from 246 to 108 companies across Norway and Sweden. This is a considerable decrease in sample size. However, it is our opinion that the benefits of matching outweigh the disadvantages from reduced sample size. The main reasons for this are due to the significant reduction in sample imbalance after matching, as described in chapter 3.1. It follows that the L_1 statistics measuring sample imbalance is reduced from 0.613 to 0.259 which is a considerable reduction.

Table 5 displays how the sample size is reduced through matching, as well as how the imbalance measure is decreased. The reason why the balance increases is because the matching process removes observations of control units that are outliers without proper matches in the sample of treated.

STEP	SWEDISH COMPANIES	NORWEGIAN COMPANIES	TOTAL	L_1 STATISTIC
Pre matching	115	131	246	0.613
Post matching	54	54	108	0.259

Table 5: Overview of sample imbalance

4.2.3 Computing Z-scores and applying winsorization

After applying CEM on the dataset we compute the Altman and Taffler Z-scores for each company as described in chapter 3.3. The Z-scores are added in separate columns in the dataset. In order to adjust for outliers, we also create separate columns containing winsorized values of Z-scores as described in chapter 3.4.

4.3 Dataset

The final dataset is based on the initial dataset and has been pre-processed as described in the former subchapter. Each row in the dataset represents an observation of a unique company that has issued a loan through a crowdlending platform at any point in time between 2017 and 2020. Further, each observation includes the Altman and Taffler Z-scores computed based on the company's financial statements from the fiscal year prior to issuance of its first loan. The purpose of this is to evaluate the credit scores of companies that are admitted to crowdlending platforms based on information available to investors considering investing in the loan. The dataset also includes the credit risk premiums computed as interest rate minus risk-free rate. As a proxy for risk-free rate, we use the corresponding five-year treasury bond yield. Further, the dataset includes a dummy variable indicating if the company is issuing a loan in Sweden or in Norway.

Additionally, the final dataset retains three of the four variables that were used for matching. The variable "Industry" is dropped, as it is only used for matching purposes in the pre-processing stage. The variables "Size" and "Age" are retained for use in the regression analysis. These variables were somewhat coarsened in the matching process. Thus, some variation related to these variables might still be left in the dataset. However, the coarsened matching should have accounted for most of the variation, and one could argue that these variables are unnecessary to further control. The variable "Year" is retained as it is used for computing clustered standard errors.

Table 6 displays the variables in the dataset that is retained in the final dataset after processing and will be used for analysis.

VARIABLE	**NOTATION**	**DATA TYPE**
Sweden dummy	*Treated*	Binary
Altman Z-score	Z_A	Continuous
Altman Z-score winsorized	Z_A *Winsorized*	Continuous
Taffler Z-score	Z_T	Continuous
Taffler Z-score winsorized	Z_T *Winsorized*	Continuous
Credit risk premium	*CRP*	Continuous
Size	*Total capital*	Continuous
Age	*Age*	Integer
Year	*Year*	Integer

Table 6: Overview of variables in final dataset

4.4 Descriptive statistics

In this subchapter descriptive statistics will be presented. The purpose is to familiarize the readers with the data we are using in the analysis. After matching, the sample contains observations of 108 unique companies. Because we have used K-to-K matching there are equal numbers of Norwegian and Swedish companies.

4.4.1 Company characteristics

Table 7 presents an overview of the size of the companies in the sample. Size is measured as total capital in thousand NOK. It shows that the mean of total capital among all companies is about NOK 15.8 million. For Norwegian companies, the mean is about NOK 14.8 million, and for Swedish companies the mean is about NOK 16.8 million. Further, it shows that there are no companies with total capital above NOK 100 million, which is the threshold for the largest bin.

Size summary

Statistic	N	Mean	St. Dev.	Min	Pct. (25)	Pct. (75)	Max
Total capital	108	15,790.050	15,787.040	3	4,310.5	20,975.2	84,607
Total capital NO	54	14,797.570	14,655.570	3	4,153.8	20,251.2	65,928
Total capital SE	54	16,782.520	16,922.490	89	6,668.2	21,340.2	84,607

Table 7: Size summary

Table 8 presents an overview of the age distribution of the companies in the sample. Age is measured in years from establishment till the year of the reported financial statements used in the analysis. It shows that the average age among all companies is about five years and four months. For Norwegian companies, the average age is about five years and one month, and for Swedish companies it is about five years and eight months.

Age summary

Statistic	N	Mean	St. Dev.	Min	Pct. (25)	Pct. (75)	Max
Age	108	5.370	6.109	0	1.8	6	29
Age NO	54	5.074	5.613	0	1.2	5.8	26
Age SE	54	5.667	6.608	0	2	6.5	29

Table 8: Age summary

Figure 2 displays the industries in which companies in the sample operate. As we can see all companies in the sample operate in the real estate industry. The reason for this is that it was not possible to find any matches in other industries. Figure 2 also displays the distribution of reporting years in the sample data. It shows that most companies are observed in 2018. The fewest are observed in 2016. This is because the first crowdlending loan was issued in Norway in 2017, and for the few loans issued in 2017, the financial statements from 2016 are used for the companies. Companies that applied for loans on Swedish platforms before 2017 thus have no matches, and are not included in the dataset.

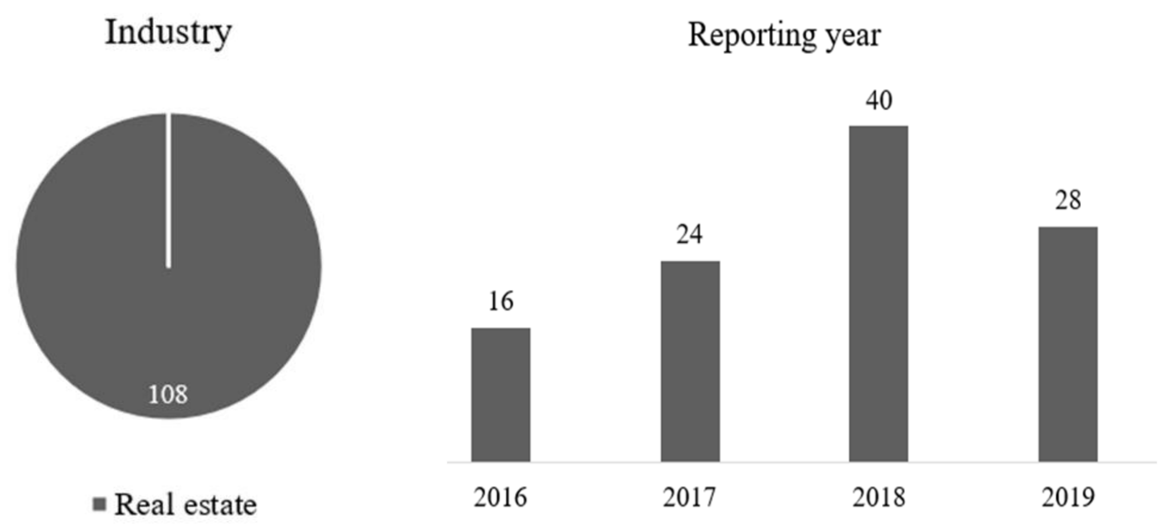

Figure 2: Industry and reporting year

4.4.2 Credit quality

Table 9 presents descriptive statistics of Altman Z-scores for the companies in the sample. The average Altman Z-score for all companies before winsorization is 7.931. After winsorization it is 6.430. For Norwegian companies, the average Altman Z-score before winsorization is 3.612. After winsorization it is 5.436. For Swedish companies, the average Altman Z-score before winsorization is 12.250. After winsorization it is 7.425. This illustrates the effect from the outlier values.

Summary of Altman Z-scores

Statistic	N	Mean	St. Dev.	Min	Pct. (25)	Pct. (75)	Max
Z_A	108	7.931	24.705	-124.773	3.169	9.622	155.711
Z_A NO	54	3.612	19.110	-124.773	2.944	8.925	45.848
Z_A SE	54	12.250	28.791	-20.163	3.693	11.543	155.711
Z_A Win	108	6.430	5.680	-3.318	3.169	9.622	19.826
Z_A Win NO	54	5.436	4.704	-3.318	2.944	8.925	19.826
Z_A Win SE	54	7.425	6.403	-3.318	3.693	11.543	19.826

Table 9: Altman Z-scores

Table 10 presents summary statistics of the Taffler Z-scores for the companies in the sample. The average Taffler Z-score for all companies before winsorization is 72.857. After winsorization it is 29.042. For Norwegian companies, the average Taffler Z-score before winsorization is -11.075. After winsorization it is 5.700. For Swedish companies, the average Taffler Z-score before winsorization is 156.790. After winsorization it is 52.384. This illustrates the effect from the outlier values.

Summary Taffler Z-scores

Statistic	N	Mean	St. Dev.	Min	Pct. (25)	Pct. (75)	Max
Z_T	108	72.857	377.724	-691.428	-6.142	30.411	2,455.891
Z_T NO	54	-11.075	155.257	-691.428	-10.639	11.521	648.006
Z_T SE	54	156.790	499.582	-97.448	0.399	52.628	2,455.891
Z_T Win	108	29.042	97.039	-76.882	-6.142	30.411	380.071
Z_T Win NO	54	5.700	63.913	-76.882	-10.639	11.521	380.071
Z_T Win SE	54	52.384	117.540	-76.882	0.399	52.628	380.071

Table 10: Taffler Z-scores

4.4.3 Credit risk premiums

Table 11 presents the interest rates and credit risk premiums for the companies in the sample. The average interest rate for all companies is 9.5%. The average interest rate is equal in both Norway and Sweden. After adjusting for the five-year treasury bond yield, the credit risk premiums are calculated. The average credit risk premium for all companies is 9.0%. For Norwegian companies, the average credit risk premium is 8.4%, and for Swedish companies the average credit risk premium is 9.7%. The reason why the average credit risk premium for Norwegian companies is lower than the average interest rate is that the Norwegian treasury bond yield for the respective time periods is positive on average. The opposite is the case in Sweden, where treasury bond yields have been negative in the respective time periods.

Summary of credit risk premiums

Statistic	N	Mean	St. Dev.	Min	Pct. (25)	Pct. (75)	Max
Interest rate	108	0.095	0.014	0.060	0.090	0.100	0.140
Interest rate NO	54	0.095	0.013	0.064	0.088	0.100	0.130
Interest rate SE	54	0.095	0.015	0.060	0.090	0.100	0.140
Credit risk premium	108	0.090	0.015	0.058	0.080	0.101	0.144
Credit risk premium NO	54	0.084	0.013	0.058	0.075	0.089	0.124
Credit risk premium SE	54	0.097	0.015	0.064	0.090	0.104	0.144

Table 11: Credit risk premiums

5. Empirical results

In this chapter the empirical results from the analysis will be described. The first subchapter presents the results from the regression models we have estimated. The second subchapter provides a summary of the results.

5.1 Regression results

The results from the estimated OLS regression models presented below are divided into three categories by their respective dependent variables. The first category includes models with Altman Z-score as dependent variable. The second category includes models with Taffler Z-score as dependent variable. The third and last subchapter includes models with credit risk premium as dependent variable. All tables report standard errors clustered by year. The same estimations with heteroskedasticity robust standard errors are presented in Appendix A 3.

5.1.1 Regression with Altman Z-score as dependent variable

Table 12 presents the outcomes from the regression models (1) through (8) which all use the Altman Z-score as dependent variable. The eight models included in the table are divided into four pairs where the first model in each pair is estimated on the unwinsorized Altman Z-score, while the second model is estimated on the winsorized Altman Z-score. Thus, model (1), (3), (5), and (7) are estimated on unwinsorized Z-scores, and model (2), (4), (6), and (8) are estimated on winsorized Z-scores.

Model (1) and (2) includes only the “Treated” dummy as independent variable, which is equal to 1 if the company is Swedish and 0 if the company is Norwegian. This implies that these models do not control further for company characteristics. This is reasonable, assuming that the matching applied in the pre-processing of data has ensured sufficient balance in the dataset. However, in order to illustrate the effect of controlling further for the coarsened variables “Age” and “Size”, these are included in different combinations in models (3) through (8). Model (3) and (4) includes the “Age” variable in addition to “Treated”. Model (5) and (6) includes the log of Total capital in addition to “Treated”. Model (7) and (8) includes both “Age” and log of total capital in addition to “Treated”.

Regression results: Altman

	Dependent variable:							
	Z_A	Z_A Winsorized	Z_A	Z_A Winsorized	Z_A	Z_A Winsorized	Z_A	Z_A Winsorized
	OLS	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	8.64^{**}	1.99^{**}	8.19^{**}	1.92^{*}	8.19^{**}	1.93^{**}	7.84^{**}	1.87^{**}
	(3.45)	(0.97)	(3.24)	(1.00)	(3.79)	(0.87)	(3.53)	(0.91)
Age			0.76	0.11^{*}			0.66	0.10
			(0.70)	(0.07)			(0.75)	(0.07)
log(Total capital)					3.49	0.48	3.13	0.42
					(4.21)	(0.42)	(4.38)	(0.44)
Constant	3.61	5.44^{***}	-0.24	4.86^{***}	-27.74	1.16	-27.89	1.14
	(2.57)	(0.67)	(3.69)	(0.85)	(39.36)	(4.21)	(39.36)	(4.25)
Observations	108	108	108	108	108	108	108	108
R^2	0.031	0.031	0.066	0.046	0.073	0.046	0.100	0.057
Adjusted R^2	0.022	0.022	0.048	0.028	0.056	0.028	0.074	0.030
Residual Std. Error	24.435 (df = 106)	5.618 (df = 106)	24.101 (df = 105)	5.601 (df = 105)	24.009 (df = 105)	5.601 (df = 105)	23.778 (df = 104)	5.594 (df = 104)
F Statistic	3.374^{*} (df = 1; 106)	3.382^{*} (df = 1; 106)	3.713^{**} (df = 2; 105)	2.523^{*} (df = 2; 105)	4.145^{**} (df = 2; 105)	2.519^{*} (df = 2; 105)	3.834^{**} (df = 3; 104)	2.108 (df = 3; 104)
Note:	*Standard errors clustered by year*							*p<0.1; **p<0.05; ***p<0.01

Table 12: Altman Z-score regressions with clustered standard errors

The coefficient for the "Treated" variable is positive and significant at a 5% significance level in all estimated models, except for model (4) which is significant at a 10% significance level. The estimated coefficients range from 7.84 to 8.64 for the unwinsorized models (1), (3), (5), and (7). For the winsorized models (2), (4), (6), and (8) the estimated coefficients range from 1.87 to 1.99. The R^2 is very low for all models and ranges from 0.031 to 0.10 across all models. Further, the control variables "Age" and log of Total Capital are non-significant across all models, except in model (4) where "Age" is significant at a 10% significance level. The constant term is significant at a 1% significance level in model (2) and (4).

5.1.2 Regression with Taffler Z-score as dependent variable

Table 13 is structured similarly to the previous table displaying results from the Altman Z-score regressions. Models (9) through (16) all use the Taffler Z-score as dependent variable. The eight models included in the table are divided into four pairs where the first model in each pair is estimated on the unwinsorized Taffler Z-score, while the second model is estimated on the winsorized Taffler Z-score. Thus, model (9), (11), (13), and (15) are estimated on unwinsorized Z-scores, and model (10), (12), (14), and (16) are estimated on winsorized Z-scores.

As in the previous table displaying results from the Altman Z-score regressions, the two first models (9) and (10) only includes the "Treated" dummy as independent variable. Again, in order to illustrate the effect of controlling further for the coarsened variables "Age" and "Size", these are included in different combinations in models (11) through (16). Model (11) and (12) includes the "Age" variable in addition to "Treated". Model (13) and (14) includes the log of Total capital in addition to "Treated". Model (15) and (16) includes both "Age" and log of total capital in addition to "Treated".

Regression results: Taffler

	Dependent variable:							
	Z_T	Z_T Winsorized	Z_T	Z_T Winsorized	Z_T	Z_T Winsorized	Z_T	Z_T Winsorized
	OLS	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treated	167.86*	46.68**	162.31*	45.24**	167.27	46.56**	162.36*	45.28**
	(99.26)	(18.65)	(95.80)	(18.39)	(100.87)	(19.62)	(96.59)	(19.06)
Age			9.37	2.44			9.38	2.45
			(7.56)	(1.69)			(7.76)	(1.80)
log(Total capital)					4.62	0.99	-0.43	-0.33
					(4.36)	(5.55)	(6.42)	(5.91)
Constant	-11.07	5.70	-58.60	-6.66	-52.60*	-3.16	-54.82	-3.74
	(22.15)	(6.44)	(52.96)	(13.02)	(28.26)	(44.19)	(34.06)	(44.53)
Observations	108	108	108	108	108	108	108	108
R^2	0.050	0.058	0.073	0.082	0.050	0.059	0.073	0.082
Adjusted R^2	0.041	0.050	0.055	0.064	0.032	0.041	0.046	0.055
Residual Std. Error	369.924 (df = 106)	94.606 (df = 106)	367.176 (df = 105)	93.864 (df = 105)	371.619 (df = 105)	95.044 (df = 105)	368.937 (df = 104)	94.313 (df = 104)
F Statistic	5.560** (df = 1; 106)	6.574** (df = 1; 106)	4.118** (df = 2; 105)	4.681** (df = 2; 105)	2.772* (df = 2; 105)	3.269** (df = 2; 105)	2.719** (df = 3; 104)	3.092** (df = 3; 104)
Note:	*Standard errors clustered by year*							*p<0.1; **p<0.05; ***p<0.01

Table 13: Taffler Z-score regressions with clustered standard errors

The coefficient for the “Treated” variable is positive and significant at a 5% significance level in all models estimated on the winsorized Taffler Z-score. Among the models estimated on the unwinsorized Taffler Z-score, the coefficient for the “Treated” variable is significant at a 10% level in model (9), (11), and (15). In model (13) the estimated coefficient for the “Treated” variable has a P-level slightly above 10%. The estimated coefficients for the “Treated” variable range from 162.31 to 167.86 for the unwinsorized models ((9), (11), (13), and (15). For the winsorized models (10), (12), (14), and (16) the estimated coefficients on the “Treated” variable range from 45.24 to 46.68. As in the Altman-regressions, the R^2 is also very low for all models and ranges from 0.050 to 0.082 across all models. The constant term is only significant in model (13) at a 10% significance level.

5.1.3 Regression with credit risk premium as dependent variable

Table 14 presents the outcomes from regression models (17) through (20) which all use the credit risk premium as dependent variable. The four models in the table include different combinations of control variables. Model (17) only includes the “Treated” dummy as independent variable. Hence, this model does not control further for company characteristics. Model (18) includes the “Age” variable in addition to “Treated”. Model (19) includes the log of Total Capital in addition to “Treated”. Model (20) includes both “Age” and log of Total Capital in addition to “Treated”.

The coefficient for the “Treated” variable is positive and significant at a 1% significance level across all models. The estimated coefficient is equal in all the models at 0.0126. This suggests that loans issued through Swedish crowdlending platforms offer 126 basis points higher credit risk premiums than loans issued through Norwegian platforms. R^2 is relatively low and ranges from 0.172 to 0.173 across all models. This indicates that controlling for age and for size only captures negligible more of the variation in credit risk premiums. This is further substantiated by the fact that none of the coefficients on the control variables are significant in any of the models. Furthermore, the intercept is significant at a 1% level in all models, and the coefficients range from 0.0817 to 0.0841.

Regression results: Credit risk premium

	Dependent variable:			
	Credit risk premium			
	OLS			
	(17)	(18)	(19)	(20)
Treated	0.0126***	0.0126***	0.0126***	0.0126***
	(0.0016)	(0.0016)	(0.0015)	(0.0015)
Age		0.00001		0.000001
		(0.0001)		(0.0002)
log(Total capital)			0.0003	0.0003
			(0.0005)	(0.0006)
Constant	0.0841***	0.0840***	0.0817***	0.0817***
	(0.0011)	(0.0013)	(0.0050)	(0.0050)
Observations	108	108	108	108
R^2	0.172	0.172	0.173	0.173
Adjusted R^2	0.164	0.156	0.157	0.149
Residual Std. Error	0.014 (df = 106)	0.014 (df = 105)	0.014 (df = 105)	0.014 (df = 104)
F Statistic	22.030*** (df = 1; 106)	10.912*** (df = 2; 105)	10.958*** (df = 2; 105)	7.236*** (df = 3; 104)
Note:	*Standard errors clustered by year*			*p<0.1; **p<0.05; ***p<0.01

Table 14: Credit risk premium regressions with clustered standard errors

5.2 Summary of results

The following subchapter presents a summary of the main results from the empirical analysis.

5.2.1 Significantly better credit quality among Swedish borrowers

The empirical analysis presented in subchapters 5.1.1 and 5.1.2 shows that companies receiving funding through Swedish crowdlending platforms have significantly higher credit quality than comparable companies receiving funding through Norwegian crowdlending platforms. The results are consistent across a wide range of different model specifications.

A total of 16 regression models were estimated, of which eight used winsorized Z-scores and eight used unwinsorized Z-scores. All models resulted in positive coefficients for the variable of interest: The “Treated” variable. The positive coefficients were significant at 5% significance level in 11 of the models, and at 10% in four models. In model (13) the coefficient had a P-value of 10.02%.

The R^2-measure was low across all models. This suggests that the estimates should not be used for prediction purposes. However, the direction of the estimates is still significant. Thus, although the analysis cannot provide efficient predictions for *how much better* credit quality the Swedish companies have, it still provides insight through the *direction of the estimates.*

5.2.2 Significantly better credit risk premiums for Swedish loans

The empirical analysis presented in subchapter 5.1.3 indicates that credit risk premiums, measured as interest rate minus the risk-free interest rate, is significantly higher in Sweden than in Norway. A total of four regression models were estimated. The results are consistent across all models. They show that credit risk premiums on loans issued through Swedish crowdlending platforms are significantly higher than in Norway. Further, the R^2 is low across all models. This suggests that the estimate should not be used for prediction purposes. However, the direction of the estimates is still significant. Thus, although the analysis cannot provide reliable estimates for *how much higher* credit risk premiums are on loans issued through Swedish crowdlending platforms, it still provides insight through the *direction of the estimate*.

6. Discussion

The findings from the empirical analysis demonstrate that there is both significantly higher credit quality and higher credit risk premiums in Sweden compared to Norway. This is an anomaly to standard economic theory, which states that loans issued to companies with relatively poorer credit quality should yield a corresponding higher credit risk premium. In this chapter, we will first discuss reasons for why the credit quality differs cross-border. Thereafter, we will discuss reasons for why credit risk premiums in Norway are lower than in Sweden.

6.1 Reasons for differences in credit quality

One potential factor that could explain the difference in credit quality is related to the use of collaterals in crowdlending. The overall risk of any given loan is a function of the risk of default and the loss given default (Kagan, 2021). In the analysis, credit quality is expressed by the Z-score which is a measure approximating the risk of default. It does not encompass any information on the loss given default. Thus, it is possible that the difference in credit quality is a result of different levels of collaterals in Norway and Sweden. As it was not possible to quantify the loss given default in Norway and Sweden due to incomplete information on collaterals, the analysis can neither confirm nor discard this possibility. Nevertheless, we argue that it is unlikely that this is the case. The reason for this is that Norwegian platforms are required to use debt collection partners in the event of default as mentioned in chapter 2.3. Debt collection partners charge between 10% and 20% of the recovered amount. Thus, investors in Norwegian loans will only receive between 80% and 90% of the principal even in the event of full recovery. This implies that Swedish loans only need collaterals of between 80% and 90% of a comparable Norwegian loan to have the same loss given default. This means that Swedish loans may have lower levels of collaterals, and still have the same loss given default as in Norway. This important regulatory difference makes it unlikely that the explanation for the difference in credit quality is related to the use of collaterals.

Another potential factor that could explain the difference in credit quality is related to regulations. As previously mentioned in chapter 2.3.1.1, Norwegian investors are currently only allowed to invest NOK 1 million per year in crowdlending, while Swedish investors do not have the same limitation. This limit may affect the type of investors that find crowdlending investments attractive. Many professional investors and financial institutions might consider crowdlending as unattractive. The reason for this is that professional investors with abundant assets under management will spend a lot of time analyzing their investments carefully, and thus want to invest higher amounts than NOK 1 million per year. Consequently, this limitation is in practice excluding professional investors from investing in crowdlending in Norway. The absence of professional investors in crowdlending may impact the credit quality. Professional investors will perform their own credit assessments of the companies borrowing through crowdlending. This will set higher demands on the crowdlending platforms to conduct proper due diligence and offer quality loans, which will improve the credit quality. Many platforms even offer loans with a guarantee of 100% subscription offered by professional investors (Kameo, 2021). Such guarantee would not have been possible to offer without professional investors' confidence in the platforms' credit assessment.

The investment limit of NOK 1 million is intended to ensure high investor protection. In practice, the limit excludes professional investors from investing in the market. This leads to less stringent assessment of companies borrowing through crowdlending. Less stringent assessment of companies means that more companies with poor credit quality can issue loans. In practice, the limit is thus reducing investor protection, contrary to its original intention. The new EU regulation also aims to protect the investors, but the regulation distinguishes between sophisticated and non-sophisticated investors, where special emphasis is placed on the non-sophisticated investors understanding the risk of the investment. Although the investment limit of NOK 1 million is meant to protect investors, the protection may be even better if crowdlending also attracts professional investors. The fact that the credit quality of companies borrowing through crowdlending in Sweden are better than in Norway, substantiates this.

In conclusion, it is our view that the difference in credit quality is a result of the current regulations. The investment limit of NOK 1 million per year excludes professional investors from investing in crowdlending. This limit makes it uninteresting for professional investors to invest in the Norwegian crowdlending market. This leaves the market dominated by retail investors who do not require as stringent credit assessments as professional investors. The outcome is that loans are subscribed even though the credit quality is poorer.

6.2 Possible mispricing of risk

Standard economic theory states that loans issued to companies with relatively poor credit quality should yield a corresponding higher credit risk premium. The fact that loans issued through Swedish crowdlending platforms have better credit quality and higher credit risk premiums thus constitute an anomaly. In the previous chapter we established that a likely reason for the relatively poorer credit quality in Norway compared to Sweden, is due to the current regulations. The investment limit of NOK 1 million excludes professional investors from investing in crowdlending. This leaves the market dominated by retail investors. Retail investors do not have the same prerequisites to understand and price risk as professional investors and financial institutions. This could explain the potential mispricing.

In conclusion, it is our view that the anomaly mispricing is a result of the current regulation, as it excludes professional investors from investing in crowdlending. This leaves the market dominated by retail investors who do not know how to properly price risk.

7. Conclusion

The purpose of this thesis is to answer the following two research questions:

(1)

"Are there any differences in credit quality between Norwegian and Swedish companies receiving funding through crowdlending?"

(2)

"Are there any differences in credit risk premiums on loans issued to comparable Norwegian and Swedish companies through crowdlending?"

To answer the research questions, we constructed a dataset containing information about companies that have received funding through Norwegian and Swedish crowdlending platforms in the period from 2017 through 2020. Observations from each country were matched using CEM in order to reduce model dependence and bias. Thereafter, we approximated each company's credit quality by computing its Z-score in line with Altman (1983) and Taffler (1983) bankruptcy prediction models. To adjust for outlier Z-scores, we applied 10% winsorization. In addition, the credit risk premium for each loan was computed. A total of 20 uni- and multivariate OLS regression models with different control variables were estimated. These established the relationship between winsorized and unwinsorized Z-scores and country of issuance, and between credit risk premium and country of issuance.

The empirical results show that the credit quality of companies receiving funding through Swedish crowdlending platforms has been significantly higher than for their Norwegian counterparts. They further show that credit risk premiums for loans issued through Swedish crowdlending platforms have been significantly higher than their Norwegian counterparts. These empirical results are consistent across all models. This concludes the two research questions.

In the discussion, we argue that the main reason explaining the relatively poorer credit quality in Norway than in Sweden is due to the current regulations. Specifically, we point at the peculiar Norwegian investment limit of NOK 1 million per year. This limit makes it uninteresting for professional investors to invest in the Norwegian crowdlending market. Since the market is dominated by retail investors who do not require as stringent credit assessments as professional investors, the loans are subscribed even though the credit quality is poorer.

The analysis shows that the credit risk premiums in Norway are lower than in Sweden, although the credit quality is poorer. This is an anomaly to standard economic theory which states that loans issued to companies with relatively poorer credit quality should yield a corresponding higher credit risk premium. In the discussion, we argue that this anomaly could be explained by the fact that the Norwegian market is dominated by retail investors without the ability to properly price risk.

Crowdlending is still an emerging form of financing. Further research on the subject is therefore necessary for the development of the industry. As future research will have access to data from a longer history of crowdlending in Norway and Sweden, both under the current and future regulations, it will be possible to use a difference-in-differences approach for isolating various effects. However, as the current Norwegian regulations have not yet been changed, such an approach is not possible at this time. One aspect that will be interesting to analyze is the impact from the new EU regulation which will be implemented.

8. Limitations

The analysis in this thesis is dependent on the sample data that is used in the analysis. Consequently, both the size and the quality of the sample are potential limitations to the results of the analysis. It is therefore important to assess these characteristics critically.

The *size* of the sample used in the analysis was primarily limited by three factors. The first factor limiting the size of the sample is related to the short active history of crowdlending in Norway and Sweden as mentioned in chapter 2.3. The short, active history implies that few companies have engaged in crowdlending activities. This is inherently limiting the number of loans and companies that can be analyzed. The only way to increase the bound from this limitation is to wait. However, it is our opinion that an empirical analysis of the Norwegian and Swedish crowdlending market offer valuable insights although the historic data is limited.

The second factor limiting the size of the sample is related to access to data as described in chapter 4.1. Two out of the six identified relevant crowdlending platforms refused to share information about previously issued loans. This prevented us from compiling a completely exhaustive dataset of all loans issued in both countries. It is possible that these platforms have issued loans to companies with either credit quality that on average differs from the companies we have observed. Although this constitutes a potential source of bias, we have not found any reliable information indicating that the platforms have different credit policy than their peers. In our opinion this limiting factor therefore does not prevent our study from providing valid results.

The third factor limiting the size of the sample is related to the choice of applying CEM in the pre-processing of data. As described in chapter 4.2, this reduced the sample size from 246 to 108 companies. Simultaneously, it also reduced the sample imbalance considerably from an L_1 measure of 0.613 pre-matching to 0.259 post-matching. Thus, the sample used in the analysis suffers from considerably less model dependence and bias than it would have without matching. This is in line with both Iacus et. al. (2012) and King and Nielsen (2019). It is therefore our view that the decision of applying CEM was reasonable.

Further, the *quality* of the sample is potentially limited by two factors. The first factor potentially limiting the quality of the sample is related to the data collection process. As no comprehensive database with data on companies receiving funding through crowdlending in neither Norway nor Sweden exists, we were forced to collect the data ourselves. The quality of the data is therefore limited by the variety of sources we have used, as described in chapter 4.1. Crowdlending platforms could for example potentially have deleted or hidden selected loans from their datasets in order to give an impression of superior performance. However, data manipulation such as this is close to impossible to identify. Thus, in our view it is not reasonable to assume that this is the case.

The second factor potentially limiting the quality of the sample is related to the financial data our analysis is based upon. Many of the companies in our sample are exempt from mandatory audit of financial statements due to small size. Appendix A 2 presents an overview of the fraction of companies that fall into this category. For these companies, the management and board of directors are the only guarantors for the reliability of the financial statements. It is therefore possible that financial statements used in the analysis could include misreporting due to errors in the accounting. In the worst cases financial statements could include straight out manipulated data. However, this is a risk suffered from everyone analyzing publicly available financial data from SMEs. In our opinion the value from the analysis outweighs the risk of misreported data.

Based on this discussion, we are of the opinion that the sample used in the analysis has sufficient size and quality.

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Appendix

A 1 Debt collection partner

Norwegian crowdlending platforms are required to use a debt collection partner in the event of default. This partner requires a share of the amount collected. The share depends on which risk class the loan belongs to. Figure 3 below shows the debt collection partner's share of recovered amount for the Norwegian platforms.

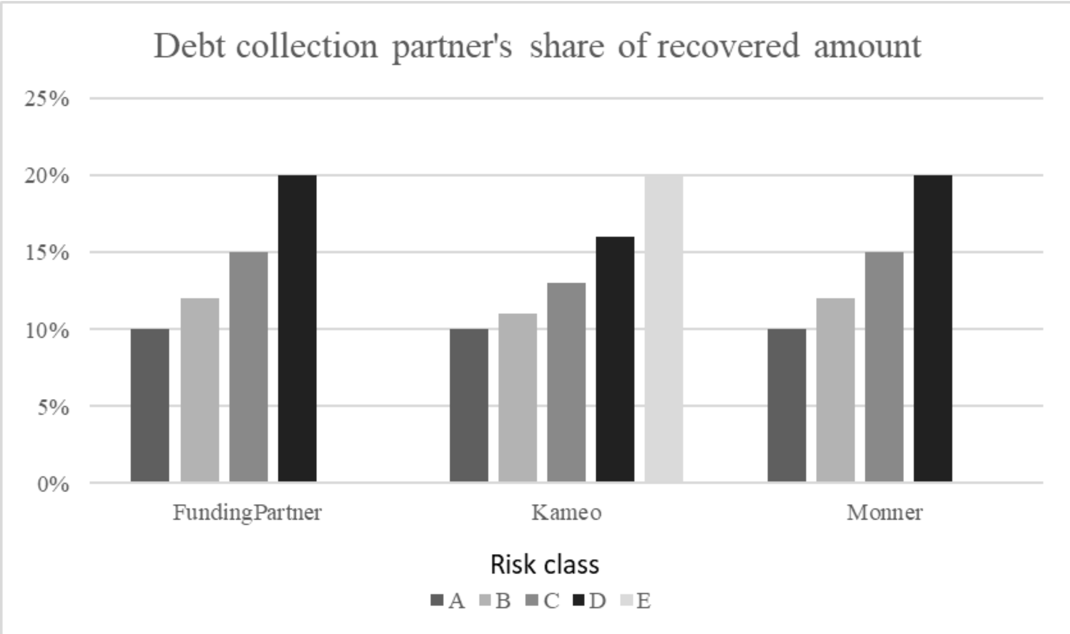

Figure 3: Debt collection partner's share of recovered amount

A 2 Audit obligation

As a general rule, companies in Norway and Sweden are subject to an audit obligation. However, there are exceptions to this rule. In Norway, companies that meet the following requirements are not obligated to be audited: (1) Less than NOK 6 million in revenue, (2) Less than ten man-years, and (3) Less than NOK 23 million of total capital (Lovdata, 2011; Lovdata, 2018). In Sweden, companies that meet the following requirements are not obligated to be audited: (1) Less than SEK 3 million in revenue, (2) Less than three man-years, and (3) Less than SEK 1.5 million in total capital (Riksdagen, 1999).

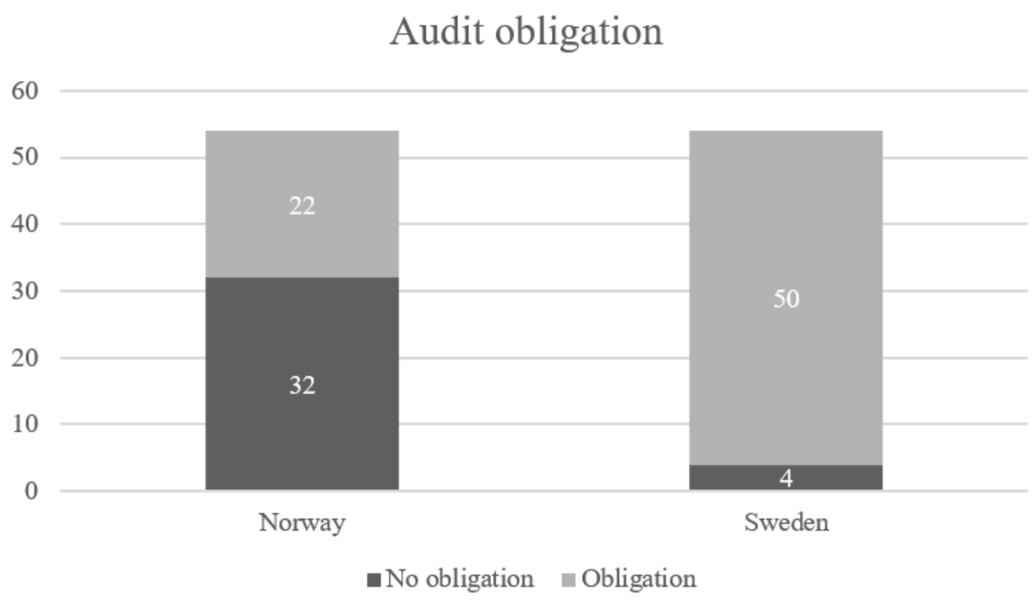

Figure 4: Share of companies subject to mandatory auditing

A 3 Regression models with heteroskedastic robust standard errors

In the main analysis we report standard errors clustered by the year-level. The tables below present the same models as in the main analysis only with heteroskedastic robust standard errors (HC3).

Regression results: Altman

	Dependent variable:							
	Z_A	Z_A Winsorized	Z_A	Z_A Winsorized	Z_A	Z_A Winsorized	Z_A	Z_A Winsorized
	OLS	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treated	8.64^{*}	1.99^{*}	8.19^{*}	1.92^{*}	8.19^{*}	1.93^{*}	7.84^{*}	1.88^{*}
	(4.75)	(1.09)	(4.54)	(1.09)	(4.84)	(1.09)	(4.71)	(1.10)
Age			0.76	0.11			0.66	0.10
			(0.69)	(0.10)			(0.67)	(0.10)
log(Total capital)					3.49	0.48	3.13	0.42
					(5.31)	(0.40)	(5.27)	(0.41)
Constant	3.61	5.44^{***}	-0.24	4.86^{***}	-27.74	1.16	-27.90	1.14
	(2.63)	(0.65)	(4.81)	(0.81)	(50.24)	(3.82)	(50.12)	(3.86)
Observations	108	108	108	108	108	108	108	108
R^2	0.031	0.031	0.066	0.046	0.073	0.046	0.100	0.057
Adjusted R^2	0.022	0.022	0.048	0.028	0.056	0.028	0.074	0.030
Residual Std. Error	24.435 (df = 106)	5.618 (df = 106)	24.101 (df = 105)	5.601 (df = 105)	24.009 (df = 105)	5.601 (df = 105)	23.778 (df = 104)	5.594 (df = 104)
F Statistic	3.374^{*} (df = 1; 106)	3.382^{*} (df = 1; 106)	3.713^{**} (df = 2; 105)	2.523^{*} (df = 2; 105)	4.145^{**} (df = 2; 105)	2.519^{*} (df = 2; 105)	3.834^{**} (df = 3; 104)	2.108 (df = 3; 104)
Note:	*Heteroskedasticity robust standard errors (HC3)*							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 15: Altman Z-score regressions with heteroskedastic robust standard errors

Regression results: Taffler

	Dependent variable:							
	Z_T	Z_T Winsorized	Z_T	Z_T Winsorized	Z_T	Z_T Winsorized	Z_T	Z_T Winsorized
	OLS	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*	*OLS*
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Treated	167.86**	46.684**	162.31**	45.24**	167.27**	46.56**	162.36**	45.28**
	(71.86)	(18.38)	(70.31)	(18.23)	(71.53)	(18.44)	(70.29)	(18.37)
Age			9.37	2.44			9.38	2.45
			(7.81)	(2.09)			(7.85)	(2.09)
log(Total capital)					4.62	0.99	-0.43	-0.33
					(10.05)	(5.77)	(9.96)	(5.73)
Constant	-11.08	5.70	-58.60	-6.66	-52.60	-3.16	-54.82	-3.74
	(21.33)	(8.78)	(45.27)	(13.79)	(85.31)	(53.00)	(88.00)	(53.32)
Observations	108	108	108	108	108	108	108	108
R^2	0.050	0.058	0.073	0.082	0.050	0.059	0.073	0.082
Adjusted R^2	0.041	0.050	0.055	0.064	0.032	0.041	0.046	0.055
Residual Std. Error	369.924 (df = 106)	94.606 (df = 106)	367.176 (df = 105)	93.864 (df = 105)	371.619 (df = 105)	95.044 (df = 105)	368.937 (df = 104)	94.313 (df = 104)
F Statistic	5.560** (df = 1; 106)	6.574** (df = 1; 106)	4.118** (df = 2; 105)	4.681** (df = 2; 105)	2.772* (df = 2; 105)	3.269** (df = 2; 105)	2.719** (df = 3; 104)	3.092** (df = 3; 104)
Note:	*Heteroskedasticity robust standard errors (HC3)*							*p<0.1; **p<0.05; ***p<0.01

Table 16: Taffler Z-score regressions with heteroskedastic robust standard errors

Regression results: Credit risk premium

	Dependent variable:			
	Credit risk premium			
	OLS			
	(17)	(18)	(19)	(20)
Treated	0.0126***	0.0126***	0.0126***	0.0126***
	(0.0016)	(0.0016)	(0.0015)	(0.0015)
Age		0.00001		0.000001
		(0.0001)		(0.0002)
log(Total capital)			0.0003	0.0003
			(0.0005)	(0.0006)
Constant	0.0841***	0.0840***	0.0817***	0.0817***
	(0.0011)	(0.0013)	(0.0050)	(0.0050)
Observations	108	108	108	108
R^2	0.172	0.172	0.173	0.173
Adjusted R^2	0.164	0.156	0.157	0.149
Residual Std. Error	0.014 (df = 106)	0.014 (df = 105)	0.014 (df = 105)	0.014 (df = 104)
F Statistic	22.030*** (df = 1; 106)	10.912*** (df = 2; 105)	10.958*** (df = 2; 105)	7.236*** (df = 3; 104)
Note:	*Heteroskedasticity robust standard errors (HC3)*			*p<0.1; **p<0.05; ***p<0.01

Table 17: Credit risk premium regressions with heteroskedastic robust standard errors