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Understanding credit risk in Norwegian real estate crowdlending

Analysis of credit quality among Norwegian real estate crowdlending borrowers across FundingPartner, Kameo and Monio

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Master`s thesis, Economics and Business Administration, Finance

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

The Norwegian crowdlending industry has grown rapidly in the last decade, resulting in the emergence of several platforms of notable sizes. Regulations are lagging, and government instances are discussing incorporating EU directives. This thesis aims to investigate risk differences in credit classifications across Norwegian crowdlending platforms. We identify risk factors and analyze potential differences in risk related to loans issued by FundingPartner, Kameo and Monio. We analyzed differences both for the platforms overall and within the credit classifications. The results provide an overview of differences in credit assessment that may benefit the decisions of both lenders and policymakers.

The analysis is based on a manually assembled data set containing loan data, financial statements and policy rates. Our empirical analysis uses three bankruptcy models to evaluate borrowers' credit risk based on financial statements. The results from the bankruptcy models are tested to ensure significance. Moreover, we integrate project-specific risk elements such as collateral, loan size, loan term and interest rates to explain the differences we discovered. We also consider actual default rates and check if they are consistent with our empirical results.

Despite having equal credit classification, we discovered significant differences between borrowers of such loans. FundingPartner issued A-classified loans with significantly riskier borrowers than Monio, despite Monio rewarding their lenders with higher interest rates. Borrowers of Monio are overall the least risky, yet the platform hosts the riskiest borrowers in our sample. Kameo borrowers with D-classified loans are significantly less risky than Monio's. Furthermore, we observe considerable differences in the use of collateral to secure lenders in the event of default. Lastly, we compare our empirical findings against confirmed defaults.

Acknowledgments

This thesis was written as part of our Master of Science degree in Economics and Business Administration, with a specialization in Financial Economics at the Norwegian School of Economics (NHH). The topic was chosen based on our fascination with financial technology (FinTech) and the growing interest in Norway with real estate project investments through crowdlending. The process of preparing our thesis has given us an extensive understanding of this emerging financial industry. We have found the journey of finalizing this thesis to be both rewarding and challenging.

Throughout the writing period, there has been a continuous flow of newspaper articles shedding light on failed loan campaigns and how lenders have been impacted. This has strengthened our efforts as it confirms that our thesis is a relevant addition to the field.

Lastly, we wish to express our sincere appreciation to our advisor, Jøril Mæland, for her invaluable feedback and guidance throughout the development of our master thesis.

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1.0 Introduction

Financial innovations are democratizing and making finance accessible to the public. FinTech allows for more tailored financial services, increasing accessibility and reducing costs (Appaya, 2021). Raising capital is a costly and challenging process for businesses. Capital-raising strategies and sources of capital imply expenses and various commitments (Timmons & Sander, 1989). Lack of access to financial institutions has limited capital raising to high-net-worth individuals and institutional investors (World Economic Forum, 2015). The innovation of crowdfunding and –lending platforms are removing the need for standard financial brokers, mediators, or intermediates and have made capital-raising activities accessible to many firms, projects, and individuals (Mollick, 2013; World Economic Forum, 2015; Lenz, 2016). Crowdfunding and –lending platforms are not likely to replace traditional financial institutions but provide opportunities for firms that may not qualify for investments from traditional banks and venture capitalists.

Crowdlending is the activity where consumers lend money in return for interest payment and the principal over time (Zhao et al., 2019, p. 4). Financial risk is decentralized and held by lenders, unlike commercial banks that accumulate risk by having positions on their balance sheets (Lenz, 2016). Furthermore, the platform where the loans are published typically earns a fixed fee for matching borrowers and lenders, unlike traditional banks relying on the interest margin between deposit and loan rates.

Real estate crowdlending dominates the Norwegian Crowdlending market, accounting for over 50% of the total alternative finance market (Shneor, 2023). Internationally, real estate crowdlending accounted for 3% of the total alternative finance market in 2020 (Ziegler et al., 2021). Today, Norway's leading operators within real estate crowdlending are FundingPartner, Kameo, and Monio. All Norwegian online platforms administrating loans and financing must hold a license as a bank or a financial company, and no individual nor professional institution is allowed to invest more than 1 million NOK per calendar year (Finanstilsynet, 2018). Despite what is previously communicated by the platforms as unnecessary tight regulations, recent media coverage has highlighted the lack of transparency and incentive to provide information to consumers (Kjellevold, 2023a; Kjellevold, 2023b; Kjellevold, 2023c; Tangen, 2023). Nevertheless, all parties are currently positive and are welcoming new regulations for professional borrowers. While the government and relevant instances are drafting regulations, research on how the platforms operate may benefit investors' decision-making when lending through the platforms.

Due to the brief existence of crowdlending, studies and research are limited. Previous research mainly explains crowdlending mechanisms and how to succeed with crowdfunding and –lending campaigns. Mollick (2013) explored the dynamics of crowdfunding, while Lenz (2016) discusses the fundamentals of peer-to-peer lending and the emerging opportunities and risks. Moritz & Block (2014) provides a comprehensive overview of crowdfunding literature from a capital-seeking perspective. Bachmann et al. (2011) compiled the earliest literature on crowdlending, displaying various variables influencing funding success. Both Klafft (2008) and Jagtiani & Lemieux (2017) highlight issues regarding information asymmetry. Klafft questions the ability of unsophisticated investors to obtain attractive returns on their lending activity, while Jagtiani & Lemieux mentions the risk of unfair treatment and fair lending violations as consequences of the lack of supervision in crowdlending compared to traditional banks. Balyuk & Davydenko (2023) advocate that crowdlending has evolved from removing intermediaries to becoming the intermediate itself. To our knowledge, research on internal credit risk differences among crowdlending platforms has yet to be conducted.

We manually assembled a dataset to conduct our analysis. We gathered relevant information on real estate loans issued at FundingPartner, Kameo, and Monio. In addition to loan information, we collected financial statements for each borrower, resulting in a comprehensive dataset. We aimed to explore potential significant differences between these three main Norwegian crowdlending platforms. We conduct a comparative analysis of the credit risk of Norwegian crowdlending real estate borrowers and ask the following research question *"Does credit risk differ across credit classifications between Norwegian crowdlending platforms?"*. The thesis is based on Norwegian real estate borrowers. The real estate industry is a natural choice due to its majority market share and the fact that it makes the dataset homogenous in terms of industry.

We collected financial statements for all borrowers one year before each loan. We identified three bankruptcy models that were suitable for our analysis and available data: Altman`s (1968) Z-score, Ohlson`s (1980) O-score, and Zmijewski`s (1984) X-score. We examine each model in detail to ensure its validity for our sample and provide a rationale for using bankruptcy models based on financial statements, along with relevant research and re-estimation of the models. Furthermore, we explain the Mann-Whitney U test and its applicability in this thesis.

Our empirical results suggest that Monio are more hesitant to classify loans as A or B, compared to FundingPartner. A- and B-classified loans at Monio are significantly less risky than borrowers with A- and B-classified loans at FundingPartner. Additionally, lenders at Monio receive a higher interest rate than lenders at FundingPartner, for A-classified loans. Paradoxically, Monio has significantly riskier borrowers with D-classified loans than Kameo. Hence, Monio has both the least risky and the riskiest borrowers. These results will be discussed regarding project-specific risks and actual losses due to defaults. To our knowledge, no instances ensure lenders of the platform's credit classification dependability. Unsophisticated investors are presumably unable to identify differences in credit quality in borrowers, at least not differences between loans issued with equal credit classification. Lenders must rely on the platform's incentive to maintain their trust, and that it is enough to prevail over the urge to maximize their total loan volume. We believe this thesis motivates future researchers to draft propositions of regulations regarding credit assessment, and make solutions to remove the information asymmetry lenders may face.

The thesis starts with a thorough review of the background of crowdlending, concerning historical and recent developments. Furthermore, we explore existing literature regarding crowdfunding in general and more comprehensive for crowdlending. This section lays the thesis's foundation, explaining the mechanisms of crowdlending and its place in financial systems. Furthermore, the section presents crowdlending markets both internationally and nationally. Finally, we provide a brief explanation of how Norway's three main crowdlending platforms operate. Section 3 provides insight into how we gathered and compiled data into our final dataset. Before summarizing the final data set, necessary decisions and the data preparation process will be discussed. Section 4 explores relevant bankruptcy models that we can compute based on the information we possess. Additionally, we explain the econometrical techniques used. Section 5 is an overview of our empirical results, explaining in detail our findings. In section 6, limitations related to this thesis are introduced. The use of financial statements in bankruptcy modelling, lack of historical data, and errors that may occur while gathering and managing data are highlighted. Finally, our conclusion is presented.

2.0 Background

This section aims to provide a comprehensive understanding of the essential principles of crowdlending. We will also review the current state of knowledge of the industry. In addition, we provide insight into the emergence and development of peer-to-peer funding globally and in Norway. Regulatory frameworks governing crowdlending and their implications on the markets will also be discussed. Finally, recent developments and the three largest platforms in Norway will be presented.

2.1 The emergence of peer-to-peer funding and its place in the world's financial system

The history of crowdfunding can be traced back to 1997 when a British band funded their reunion through online donations. In some circumstances, peer-to-peer funding and lending had occurred before, but this instance led to the platform ArtistShare launching in 2000 (Zhao et al., 2019). ArtistShare evolved into a fundraising platform for projects related to music, film, and photography. Several crowdfunding and –lending platforms launched in the following decade. Fast forward to 2020, and the market size of crowdfunding worldwide reached 114 billion USD, forecasted to double by 2028 (Statista, 2019; Ziegler et al., 2021).

Crowdfunding can be divided into two main categories: commercial and non-commercial (Lenz, 2016). Non-commercial crowdfunding is donation-based crowdfunding, such as the one funding the band reunion in 1997. Commercial crowdfunding is either equity-based crowdfunding, crowdlending, or reward-based crowdfunding. Crowdfunding activities remove the need for brokers, mediators, or intermediaries (Lenz, 2016). Mollick (2013, p. 2) defines crowdfunding as "the efforts by entrepreneurial individuals and groups – cultural, social, and for-profit – to fund their ventures by drawing relatively small contributions from a relatively large number of individuals using the internet, without standard financial intermediaries". We will describe crowdlending in more detail in the next subchapter.

2.2 Roles and mechanisms of crowdlending

Lending-based crowdfunding, peer-to-peer lending, and crowdlending are all different names for the activity where "consumers lend money in return for interest payments and a repayment of capital over time" (Zhao et al., 2019, p. 4). Unlike commercial banks that accumulate risk by taking positions on their balance sheet, crowdlending platforms decentralize the risks by spreading them to the lenders (Lenz, 2016). In addition, crowdlending platforms enable users to construct loan agreements containing the lender's credit claim to receive redemption payments and interest in the future. Lenz (2016, p. 6-8) describes the process of how platforms mediate debt capital between borrowers and lenders in six steps:

1. The borrower, either an individual or a business, indicates to the lending platform the required maturity and amount of the loan agreement.
2. The platform is assessing the underlying credit risk. If the platform finds the credit risk acceptable, it sets an appropriate interest rate and risk classification.
3. The platform publishes the offer to its user for a predefined period, given that the borrower agrees with the platform's pricing.
4. Lenders with access to the platform place their offers in portions of the required financing amount in maximum and minimum amounts set by the platform (FundingPartner, 2023; Kameo, 2023: Monio, 2023).
5. The loan is issued when the total sum of offers matches the required loan amount. Money is collected by the platform and transferred from the lenders` bank accounts to the borrower, returning the investors a credit claim as a fragmented part of the total issued loan. The credit claim is the legal documentation of the borrower's commitment to pay interest and redeem the principal in the future. Distribution of credit claims and transfer of capital is not done in advance but forwarded after the loan is issued.
6. Subsequently, the platform collects and distributes interest and redemption payments from the issuance until the loan's maturity. The structure of the loan varies from a monthly annuity to acting as a bond. If the borrower defaults, the platform must arrange the collection of payments on behalf of the lenders. The platform is not liable for losses borne by lenders but does, in some instances, arrange a sale of the default loans on behalf of the lenders to minimize the loss of the credit claim.

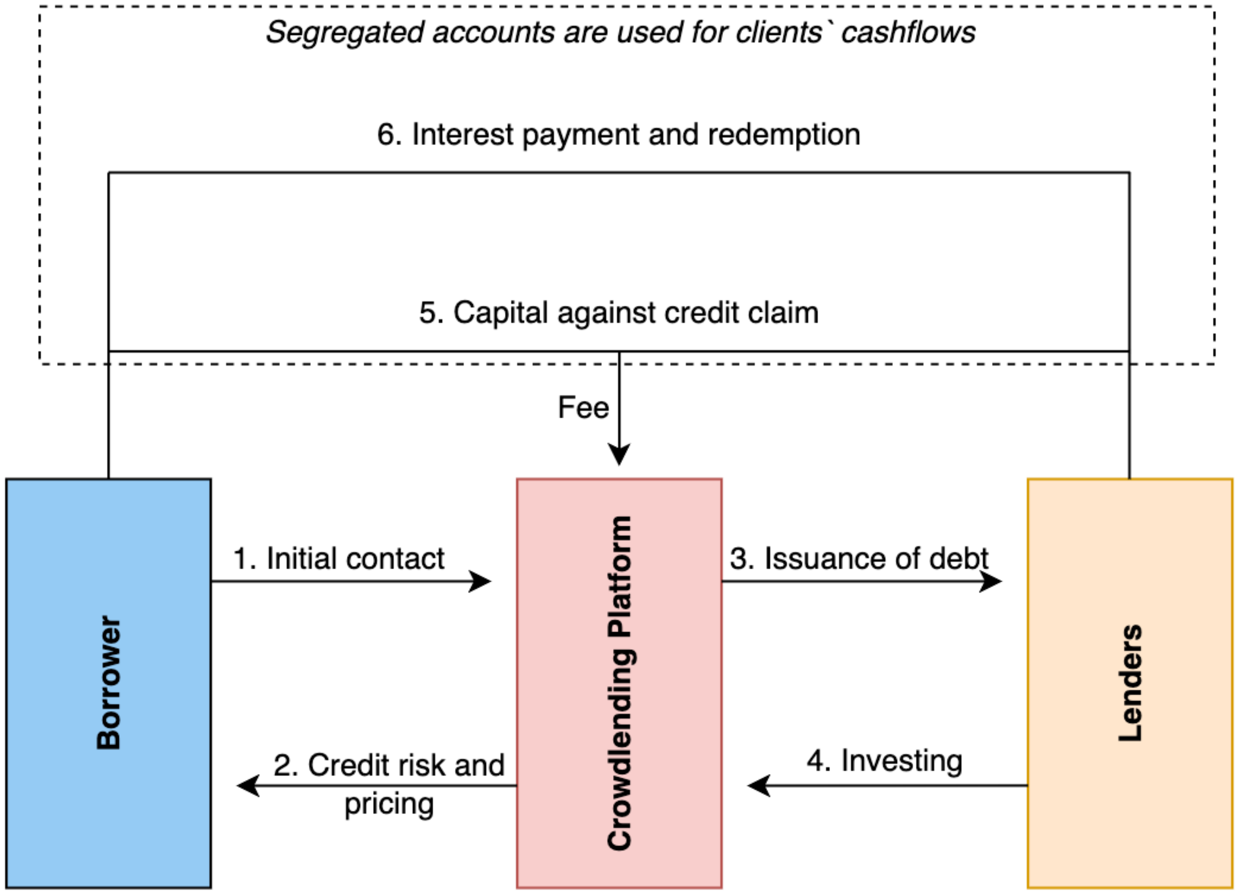

Figure 2.1: The steps in the crowdlending process (Lenz, 2016, p. 6-8).

Unlike the banking business, which relies on earning the interest margin between deposit and loan rates, the crowdlending platform's business model is independent of changes in interest rates (Lenz, 2016). The platforms receive a fee for matching borrowers and lenders. This fee is collected in different forms, depending on the platform, but generally, it is collected as a premium of the interest that borrowers pay to lenders (Lenz, 2016; FundingPartner, 2023; Kameo, 2023: Monio, 2023). Other than the apparent low operational costs compared to banks, platforms are not required to fund portions of issued loans with their equity, and there is no need for an equity buffer to absorb losses. Removing the credit risk from their balance sheet allows crowdlending platforms to operate with lower fees and less capital (Lenz, 2016). In addition, a growing number of crowdlending platforms have started organizing secondary markets where investors can trade their loans, making their loan portfolios more liquid. This facilitates institutional investors that require more asset liquidity than retail investors. New EU regulations will also allow platforms to use *bulletin boards*, which display interest in buying and selling secondhand loans between investors (Regjeringen, 2021b).

Given the limited information about borrowers and the platforms` credit quality assessment, lenders must trust the platforms (Lenz, 2016). To ensure trust between lenders and platforms, there is a need for transparency and disclosure of all relevant information regarding the borrowers and the risk elements associated with the loans. In traditional banking, the lending decision is based on analyzing multiple factors, such as income, statements, tax reports, balance sheets, and partly personal relationships through interviews or long-time relations. However, the personal relationships between lenders and borrowers cannot be easily forged in crowdlending due to the inherent constraints of time and the platform's nature (Lenz, 2016). This results in a lack of crucial information for investors. Both borrowers and platforms are incentivized not to publish all risk elements in their entirety, as their goal is to fill the loan. In addition, the platforms are incentivized to increase transaction volume due to the income generated by a fee usually proportional to the transaction volume. Hence, there are apparent conflicts of interest between the platform business model and the protection of investors (Lenz, 2016).

Lenz (2016) argues that the intuition that borrowers tend to have poor credit quality and/or history, which makes them unable to finance their projects through traditional banks, is untrue. It is not always the case that platforms generally accept higher risks than traditional banks. Previously bank manager Truls Blakstad at Nordea stated that they require 50% equity for land purchases (Brun, 2016). They also require pre-sale with 10% in pre-payment and that the sale should be conducted by a pre-approved real estate agent. The Norwegian crowdlending platforms we have investigated do not require pre-sales of real estate projects and can offer a higher debt share than traditional banks (FundingPartner, 2023; Kameo, 2023; Monio, 2023). The credit assessment differs notably. The divergence in credit risk assessment may lead to borrowers' being rejected from banks proceeds to apply for loans in crowdlending platforms. We will elaborate more comprehensively on how crowdlending platforms assess credit risk and set proper loan rates in the next subchapter.

2.2 Credit classification and interest rates

Companies seeking funding on Norwegian crowdlending platforms get their credit rated. This credit classification determines the loan rate and whether the company will get its campaign published (FundingPartner, 2023; Kameo, 2023; Monio, 2023). These loans have a limited upside potential equal to the loan's interest rate. Thus, managing risk and downside potential is crucial. An investment's total upside potential is reached if the borrower pays back the loan in full in addition to the interest rates. The downside potential with these investments occurs when borrowers have severe payments or liquidity issues resulting in bankruptcy, hence cannot pay back either the principal or interest rates. It is, therefore, essential for lenders that the platforms conduct a thorough credit risk assessment for all borrowers and assign correct interest rates and credit classification for borrowers. Interest rates are a result of credit risk and demand. If the demand to invest in a loan is low, the loan rate must increase to fulfil it. FundingPartner (2023), for instance, distributes emails to inform investors of changes in loan rates to attract new lenders to specific loans.

2.3 State of knowledge: research overview

This subchapter will provide an overview of the state of knowledge in the industry. Existing literature gives insight into the emergence of crowdfunding, the establishment of crowdfunding platforms, crowdfunding's place in the financial system, key roles, and mechanisms. These factors affect borrowers' probability of successful funding campaigns, their interest rate of such campaigns as well as the relationship between borrowers' characteristics and campaign success.

Mortiz & Block (2014) and Bachmann et al. (2011) have compiled a thorough literature review of the scientific research on crowdfunding. Moritz & Block focuses on firms as capital-seeking parties, while Bachmann et al. Brought literature on peer-to-peer lending to light. Researchers have shown significant interest in motives for participation in crowdfunding markets for both capital seekers and providers (Moritz & Block, 2014). However, initial research in the field focused on identifying variables that influence funding success and interest rates of loan requests (Bachmann et al., 2011). Bachmann et al. suggested that future research on the influence of the borrowers' loan descriptions on funding success is necessary. Additionally, Moritz & Block (2014) indicated that studies on the role of crowdfunding platforms, their optimal business models, and quantitative studies based on empirical market data are limited.

Klafft (2008) indicated in the initial phase of crowdlending platforms' existence that information asymmetry is a critical issue. Klafft questions the ability of inexperienced lenders to obtain attractive returns on their investments and provides investment rules to improve profitability. In addition to potential information asymmetry, the lending platforms are not subject to the same supervision as traditional banks (Jagtiani & Lemieux, 2017). This allows for faster and lower-cost credit assessment, potentially carrying a risk of unfair treatment and fair lending violations. Jagtiani & Lemieux (2017) describe how previous researchers have studied the price of credit in crowdlending. Comparison of credit classification and interest rates for crowdlending versus traditional banks for business and consumer loans has been of great academic interest. Balyuk & Davydenko (2023) also describe how crowdlending has evolved from removing intermediaries to becoming the intermediate itself, where investors solely rely on the platform's evaluation of borrowers.

Researchers are primarily interested in understanding how to succeed with crowdfunding and – lending for capital providers and seekers. Crowdlending's place in the financial system compared to traditional banks has been thoroughly discussed in research. Mortiz & Block (2014) request further empirical market data studies. The researchers also state that estimating the default probability in crowdfunding markets is challenging due to the asymmetric information between the parties. Despite the apparent information asymmetry, Balyuk & Davydenko (2023) identified that over 98% of investors agree to fund loan applications on offer. The platforms' reliance on trust is a crucial adjusting factor to their incentive to boost volumes and, thus, its fees.

2.4 International markets

Crowdlending is a global phenomenon, with platforms operating in most countries (Shneor et al., 2020). This section will describe how crowdlending has developed globally in the last decade. In descending order, the three biggest markets were previously China, the United States, and the United Kingdom (Ziegler, 2020, p. 35). The Chinese market was dominated by consumer lending, and as much as 67% of the volume came from consumer lending. The rest of the market consisted of business lending, heavily concentrated on real estate lending (Shneor et al., 2020, p. 51). Pre-2016, the Chines' crowdlending market was unregulated, leading to exponential growth in transaction volumes and platforms, leading to over 2000 crowdlending platforms by 2015 (Milne & Parboteeash, 2016, p. 18). Ezubo, a major crowdlending platform failed in 2016, and $11 billion perished. This led to regulatory changes and an increased concern about fraud in the market. The regulation changes led to a steep decline in volume and global market share. The Chinese market accounted for 48% of the global volumes in 2019. One year later, their global market share shrunk to only 1% (Ziegler, 2021).

The United States and the UK have been the pioneers in developing the crowdlending market. In 2020 the US became the largest alternative finance market in the world, with 65% of the global market share, reaching a total transaction volume of more than $73 billion (Ziegler, 2021, p. 28). Just above $2 billion was related to real estate lending.

Unlike China, the US crowdlending market has been regulated since the emergence of the industry. The SEC required in 2008 that all crowdlending loans should be registered as a security (Shneor et al., 2020). This was the first-ever regulation of the crowdlending market. In addition, the Jobs Act of 2012, which governs the crowdlending market, strongly emphasizes the broker/intermediary model (Shneor et al., 2020, p. 53). Therefore, the US market tends to rely on selling complete or partial loans to professionals and institutional investors instead of connecting retail individuals with borrowers (Milne & Parboteeash, 2016). As a result, the platforms operate more like a syndicate, establishing a system to match loan notes with potential investors (Shneor et al., 2020).

2.5 The Norwegian market

This subchapter will describe crowdlending's development in Norway over the last decade. The Norwegian crowdlending market was established years later than the Chinese and US markets. Kameo issued the first Norwegian crowd-based loan in 2017 (Weldeghebriel, 2018). Today, the Norwegian crowdfunding market is growing rapidly, although it remains minor compared to the conventional banking sector. As of March 2023, the traditional banking industry has a total of 1,830 billion NOK in loans to Norwegian businesses, where 851 billion NOK is related to real estate and construction (SSB, 2023c). From 2016 to 2022, the crowdfunding market has grown from 45 million NOK to 2.35 billion NOK (Shneor, 2023, p. 2).

In Norway, the most popular form of crowdfunding is lending projects within real estate. Loans to real estate-related projects accounted for 47% of the market in 2021. By 2022, the market share grew to 56% of the total alternative finance market (Shneor, 2023, p. 2). Kameo (2023) states that the popularity is due to both convenience and long-term necessity of household.

Since the first loan issued by Kameo in 2017, many platforms have emerged in the market. The largest platforms in Norway as of March 2023 is FundingPartner, Monio and Kameo. FundingPartner and Monio both issued their first loans in 2018. In 2022, FundingPartner had a total volume of 740 million NOK distributed on 192 loans. FundingPartner has experienced substantial growth from its start in 2018 and is today the largest crowdlending platform based on volume in Norway, followed by Monio (FundingPartner, 2023; Monio, 2023). Kameo has not experienced the same growth in the Norwegian market as its peers but has a strong position in the Scandinavian market. Only 14% of Kameo's total volume is from the Norwegian market (Kameo, 2023).

FundingPartner, Kameo and Monio are entirely or partially owned by traditional financial institutions. Monio is owned by Sparebank 1 Sr-Bank ASA, while FundingPartner is co-owned by DNB through its venture capital firm with an ownership stake of 10% (Proff Forvalt, 2023). Kameo is partially owned by ABG Sundal Collier Holding ASA, a Norwegian Investment Bank. The significant presence of traditional loan brokers and capital suppliers in the crowdlending market is apparent from their investments, helping them strengthen their position as an essential part of the Norwegian capital market. The platforms can also use their owners as strategic partners and utilize their excessive knowledge of capital markets.

2.6 Regulations

This subchapter will describe current regulations and how relevant instances work on drafting future regulations. Multiple regulatory measures have been implemented following the initiation of crowdlending activities in Norway. The Norwegian crowdlending market is regulated by The Financial Supervisory Authority, as there are no separate laws or licensing for crowdlending platforms (Finanstilsynet, 2017, p. 2). All platforms administrating loans and financing through an online platform must hold a license as a bank or a financial company. Regulations were tightened in 2019, preventing individual and professional institutions from investing over 1 million NOK during a full calendar year (Finanstilsynet, 2018). This has resulted in fewer large loans being issued, as institutional investors will reach the limit fast and effectively, reducing the market's growth potential (Skjelsbæk, 2022). The current regulations limit the platform's ability to help investors automatically invest their funds, known as auto-investing (Finanstilsynet, 2017). This regulation reduces diversification and increases the lender's risk.

In October 2020, the EU created a uniform regulation for all members, which was later accepted by the European Free Trade Association, including Norway (Regjeringen, 2021a). The new legislation set a maximum value of €5 million yearly loans for each borrower (Regjeringen, 2021b). The new legislation created a new separate law for crowdfunding platforms. Platforms no longer need to hold a bank or financial company license. The new regulations will make it easier for suppliers to act according to customer regulations for crowdfunding purposes in Norway (Regjeringen, 2021b).

The legislation aims to make it easier and cheaper to conduct cross-border lending between nations in the EU and EFTA (Regjeringen, 2021b). As a result, investors can diversify their portfolios, reducing risk, while borrowers are more likely to subscribe to their loans fully. The legislation will also make a distinct separation between sophisticated and non-sophisticated investors. This distinction is made in investors' best interest to secure adequate knowledge related to these types of investments. The crowdlending platforms must inform non-sophisticated investors of risks, test their knowledge, and simulate investors' ability to handle losses (Regjeringen, 2021b). The process of implementing the new legislation in Norwegian law is, as of February 2023, still not finalized. Today's Norwegian law of a maximum of 1 million NOK for each investor will also be terminated, resulting in a significant growth potential for the market in future years. The new European legislation has been well received by the crowdfunding industry in Norway. Geir Atle Bore, the founder and CEO of FundingPartner, states that much of the projected growth in the industry is pending on this new legislation (Skjelsbæk, 2022). Recent media development has highlighted the need for proper regulations, as explained in the next subchapter.

2.7 Recent developments

Until February 2023, most issued loans were fulfilled on the day of issuance (FundingPartner, 2023; Kameo, 2023; Monio, 2023). Recent media coverage has enlightened the potential problems related to asymmetrical information. Heyerdahl (2023) published the first of several articles shedding light on the fact that Monoi's largest borrower by total loan amount formerly had 11 bankruptcies. The journalist highlighted that real estate has been booming in recent years and that interest rate hikes and declining sales for real estate developers are putting pressure on crowd-financed projects.

More than a dozen newspaper articles spanning from the 25th of February this winter, including statements and comments from investors, platforms, professors, government instances, journalists, borrowers, and clients of the real estate borrowers, shed light on potential issues of crowdlending. Investors are remarking on the lack of information and that Sparebank 1 SR-Banks ownership strengthens the investors' belief that loans issued by Monio are a safe investment (Kjellevold et al., 2023a). Professor Andreassen at NHH states that Monio is placing the risk on retail investors by not controlling borrowers' information before issuing loans on their platform (Kjellevold et al., 2023b). The Norwegian consumer council states that Monio has not complied with their obligation towards their investors (Tangen et al., 2023). Monio, despite acknowledging that they did not know the complete track-record of the borrower in focus, is arguing that the information stated is sufficient. The main issue is that investors that have or are experiencing losses are remarking on the lack of information. In contrast, the platform and borrowers state that the information provided is sufficient.

Monio's largest borrower, Amundsen (2023), responds that his projects are affected negatively by the negative coverage, damaging the retail investors and the platform itself. As a result, platforms struggle to fulfil newly issued loans (FundingPartner, 2023; Kameo, 2023; Monio, 2023). FundingPartner, Kameo, and Monios state that their losses accumulate to 0.36%, 0.12%, and 0.75%, respectively. As illustrated by Google Trends (n.d.) searches below, the negative focus is noticed by the public. Despite the moderate losses, investors seem hesitant to invest in newly issued loans.

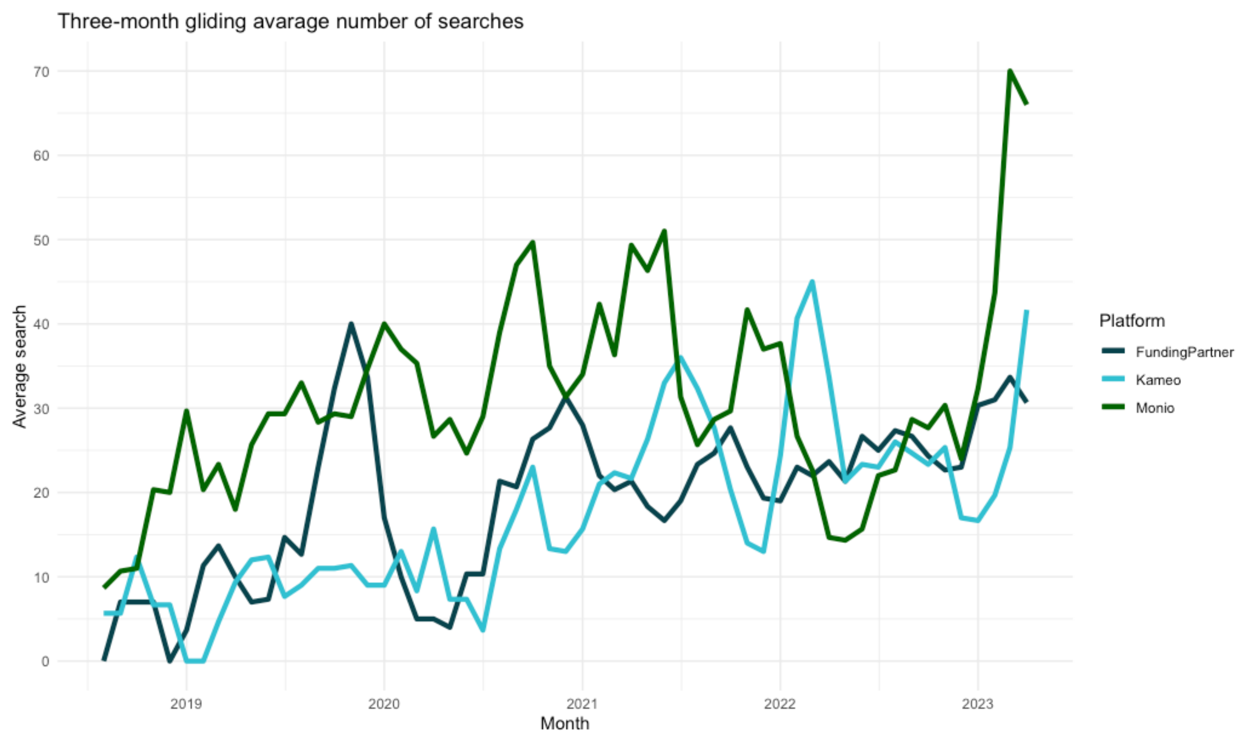

Figure 2.2: Three-month gliding average searches for the terms: FundingPartner, Kameo, Monio and Monner. Monio was previously named Monner, which is accounted for in this figure. Searches from 01.01.2018 to 01.04.23 (Google Trends, n.d.).

Monio (2023) was previously named Monner. The data is adjusted for the name change in the figure above. Monio has been the most popular search term of the three, whereas FundingPartner and Kameo experienced similar popularity. The public was approximately equally interested in the three platforms in mid-2022, but the Monio Google searches skyrocketed after the release of the first newspaper article. Recent media coverage of crowdlending, with Monio in focus, highlights the need to regulate the industry (Kjellevold et al., 2023c). All parties are positive and welcome new regulations. While the government and relevant instances are drafting regulations, research and studies on how the platform operates may benefit investors' decision-making.

2.5 The Norwegian platforms' credit classification

The following section will provide an overview of the three crowdlending platforms subject to this thesis analysis. We will describe how they conduct credit classifications, manage credit risk and handle defaults.

2.5.1 FundingPartner

According to FundingPartner (2023), only 2-5% of all applications are accepted due to their high standard of credit risk assessment. FundingPartner's credit risk team assesses all loan applications, and their credit board must approve each loan. The credit board consists of professionals with experience from leading investment banks, traditional banks, and accounting firms (FundingPartner, 2023).

Each loan has its own risk assessment, which is presented to the investors. The risk assessment presents each project's strengths, weaknesses, and potential risk factors. Risk factors related to project, sales, market, and liquidity are presented in detail. An extensive analysis of the security and collateral of the loans is also displayed. Measures implemented by FundingPartner to reduce default risk are presented if taken. Typical measures are to prohibit dividends if a loan is active or prohibit borrowers from securing new loans with better security or collateral in assets that negatively affect the security for the lenders. FundingPartner (2023) also states that loans could be subject to false information from borrowers. Even though a thorough background check is conducted on both company and key personnel, risk related to false information is present.

Based on risk related to each project, loans are given a risk classification varying from A to D. This risk assessment is also used to set the interest rate for each loan. Higher risk results in higher interest rates and vice versa. In case of a loan default, FundingPartner (2023) has a partnership with Intrum Capital which helps to retrieve funds from collateral. If a borrower is 50 days late on a payment, Intrum Capital will buy the loan from the investors for 0.5% of the loan value. A percentage of funds secured from collateral will be returned to investors based on the loan’s credit classification. 88% of the funds retrieved are returned to investors of A-classified loans, 85% to B-classified, 80% to C-classified, and 75% to D-classified.

2.5.2 Kameo

Kameo uses a four-step process for all loan applications to conduct an in-depth analysis of all debt seekers. The first step is initial screening where all essential information about the applicant is gathered electronically. A credit risk screening is also conducted through their partners, Experian and Bisnode. Only companies with satisfying credit scores are moved forward to the second step. In the second step, the applicants must complete a loan application with information about accounting details, bank statements, project estimates, board, and stockholders. The third step in the application analysis is an in-depth analysis and interview with the applicants. All information is run through Kameo`s credit classification model. The third-party credit classificationfrom Bisnode and Experian is also heavily relied on. The fourth and last step is quality control and publishing. The credit committee conducts a final assessment and approval of credit scores and interest rates. Each loan is given a risk classification from A to E. The loan is then published and becomes available for investors.

Kameo has multiple procedures in place to reduce risk. All loans are required to have collateral or security. Collateral can vary from property, stock pledge, or personal security. In case of default, investors' losses will be reduced. The LTV is limited to a maximum of 75%. In the case of a default, investors can handle a price reduction on the collateral of 25% before being negatively impacted. This information is shown under risk assessment in each campaign. The credit committee approving all loans has excessive experience in construction, accounting, and law. This approval helps to ensure the quality of all loans. In case of default, loans will be sold to Kameo's partner Intrum Capital. Their job will then be to secure funds from collateral related to the loan.

2.5.3 Monio

Monio partners with Experian to conduct all credit classifications on potential borrowers. Experian is one of the world's biggest and most prominent credit classification agencies (Monio, 2023). These credit classification reports are available to all investors. The credit score supplied by Experian indicates the risk of default. This is done to make risk assessment uncomplicated for investors. Monio also conducts in-depth assessments and background checks on key personnel in the organizations who seek funding. This can be related to experiences, references, education, and other essential information. All external information is documented and presented to investors. Information supplied by the borrowers is signed, and they are obligated to ensure that all information in the campaign is correct.

Each campaign's risk assessment presents key numeric values to investors. Typical values included are the price of purchase, building cost, estimated selling price, total debt related to the project, and loan to value based on the estimated selling price. The assessment also contains strengths and weaknesses related to the project and company. The type and size of collateral are also presented. A credit score between A and D is given based on risk related to each loan. The risk related to each loan is a crucial indicator of the interest rate.

Monio partners with Intrum Capital to retrieve funds from the collateral in case of a default. Intrum Capital will buy the defaulted loan for 0.5% of the loan value. Then, based on the loan credit risk, a percentage of the funds retrieved will be returned to investors. For example, 88% of the funds retrieved will be returned to investors if an A-rated loan defaults. In the case of a B-rated loan default, 85% will be returned, 80% for C-rated, and 75% for D-rated (Monio, 2023).

3.0 Data

This section describes the data we will analyze and how we gathered and processed it. We will also describe relevant decisions we had to make during the data gathering and processing. Finally, descriptive statistics will be presented on critical metrics to summarize the original and final data set to present omitted observations.

3.1 Data collection

This thesis is based on a self-constructed dataset containing information on each real estate loan issued by FundingPartner, Kameo and Monio. The dataset includes financial statements related to each borrower. Due to the brief existence of crowdlending, historical data is severely limited. The limited data and lack of incentives for crowdlending platforms to provide the public or researchers with data hinder this and future research. Nevertheless, we managed to assemble a satisfactory dataset to conduct our analysis.

3.1.1 Collection of loan data

There is no database containing a collection of loan data from Norwegian crowdlending platforms. FundingPartner (2023), Kameo (2023) & Monio (2023) have accessible information on all issued loans back to 2018. To access this data, we were required to sign up as users on FundingPartner and Kameo. All loan-related data was manually gathered from the platform's websites. Monio had accessible loan details without signing up. The data we could extract from the platforms web site were the legal name of the borrower, region of the project, loan identification number, loan size, interest rate, risk class, terms in months, whether there was a personal-, group guarantee or project collateral guarantee and priority, as well as date of issuance. Group guarantee is the term we use if there is collateral in firms beyond the borrowing firm. FundingPartner also included the number of investors per loan. LTV was provided for some loans. FundingPartner, Kameo, and Monio had respectively 299, 109, and 381 real estate loans by 31.12.22, compiled into an initial dataset of 789 loans.

3.1.2 Collection of financial statements and interest data

The collection of loan data includes the legal name of all borrowers, allowing us to collect each borrower's financial statements. FundingPartner, Kameo, and Monio had 122, 39, and 56 unique borrowers, respectively, from their first issuance until 31.12.22. Two firms borrowed from FundingPartner and Monio, and two firms borrowed from both FundingPartner and Kameo. Finally, three firms borrowed from both Kameo and Monio. Accounting for overlapping firms, we have extracted financial statements for 161 unique borrowers. The collection of financial statements was done through Proff Forvalt (2023), dating from 2016 to 2021. The financial statements of each borrower were merged into the dataset, containing all information regarding the relevant issued loan and available public accounting information.

Table 3.1: Overview of observations before and after omitting observations. Number of omitted observations is presented in paratheses.

	Number of loans - Original dataset				Number of loans - Final dataset			
Year/Platform	**FundingPartner**	**Kameo**	**Monio**	**Total**	**FundingPartner**	**Kameo**	**Monio**	**Total**
2018	3 (3)	1 (1)	13 (13)	**17 (17)**	0	0	0	0
2019	22 (6)	10 (3)	36 (6)	**68 (15)**	16	7	30	**53**
2020	35 (9)	10 (1)	67 (7)	**112 (17)**	26	9	60	**95**
2021	90 (15)	39 (13)	140 (26)	**269 (54)**	75	26	114	**215**
2022	149 (11)	49 (10)	125 (11)	**323 (32)**	138	39	114	**291**
Total	**299 (44)**	**109 (28)**	**381 (63)**	**789 (135)**	**299**	**109**	**381**	**654**

We have retrieved credit scores from Proff Forvalt (2023) for all companies where we have had access to complete accounting details for one or several years. These credit classifications are based on several factors, including accounting numbers, stockholder information, board information, loan encumbrances, and default remarks. The credit scores are presented in two forms, a letter grade and a numeric score. The letter grades range from A++ to C, while the numeric score ranges from 100 to 0 (Proff, 2023).

The daily policy rate was retrieved from Norges Bank (2023) and merged on the date in the compiled dataset. A general price index was necessary for one of our chosen bankruptcy models. Therefore, we collected GNP data from SSB (2023a) to the price index where 2015=100.

3.2 Data processing

To prepare the data for analysis, we took several measures to clean the data. This section outlines the essential steps taken to prepare the data for analysis.

3.2.1 Data processing and decisions made during the data gathering

Financial statements must be available in the year prior to issuing the relevant loan to conduct an analysis based on borrowers' financial statements. The lack of financial statement data is caused by companies being established in the year of issuance. As stated earlier, FundingPartner, Kameo, and Monio had 122, 39, and 56 unique borrowers by 31.12.22 before omitting companies lacking financial statements. After omitting, the respective companies' unique borrowers were reduced to 97, 28, and 43. 135 loans were related to companies that lacked financial statement data the year before loan issuance, resulting in a final dataset of 657 observations.

3.3 Final dataset

The final dataset contains 657 observations ranging from 1.1.2019 to 31.12.2022. All relevant available loan data, financial statement data, and external data that we will use when analyzing the three crowdlending platforms, FundingPartner, Kameo, and Monio, are included and processed.

Table 3.2: Overview of the total sum of loans from 2018 to 2022. The first table is for the whole dataset while the last table is after omitting variables, resulting in our final dataset.

Sum of loans - Original dataset

Year/Platform	FundingPartner	Kameo	Monio	Total
2018	10.200.000	2.350.000	27.217.000	**39.767.000**
2019	70.800.000	42.050.000	82.974.000	**195.824.000**
2020	128.000.000	43.200.000	128.134.880	**299.334.880**
2021	337.950.000	155.374.000	344.666.506	**837.990.506**
2022	579.950.000	174.339.500	323.718.067	**1.078.007.567**
Total	**1.126.900.000**	**419.313.500**	**906.710.453**	**2.452.923.953**

Sum of loans - Final dataset

Year/Platform	FundingPartner	Kameo	Monio	Total
2018	0	0	0	**0**
2019	53.500.000	27.450.000	64.112.500	**145.062.500**
2020	84.900.000	39.700.000	104.942.880	**229.542.880**
2021	281.000.000	105.774.000	268.200.843	**654.974.843**
2022	528.350.000	132.428.500	293.831.266	**954.609.766**
Total	**947.750.000**	**305.352.500**	**731.087.489**	**1.984.189.989**

The tables below show key metrics before and after omitting observations about companies lacking financial statements before the loan issuance year. As mentioned earlier, 135 observations were omitted, resulting in a total volume of about 470 million NOK worth of loans. Eliminating these loans impacted key metrics such as average loan size and loan rates.

Table 3.3: Average loan size before (original) and after (final) omitting observations.

Average loan size - Original dataset

Year/Platform	FundingPartner	Kameo	Monio
2018	3.400.000	2.350.000	2.093.615
2019	3.218.182	4.205.000	2.304.833
2020	3.657.143	4.320.000	1.912.461
2021	3.755.000	3.983.949	2.461.904
2022	3.892.282	3.557.949	2.589.745

Average loan size - Final dataset

Year/Platform	FundingPartner	Kameo	Monio
2018	0	0	0
2019	3.343.750	3.921.429	2.137.083
2020	3.265.385	4.411.111	1.749.048
2021	3.746.667	4.068.231	2.352.639
2022	3.828.623	3.395.603	2.577.467

Table 3.4: Average loan rates before (original) and after (final) omitting observations.

Average loan rates - Original dataset			
Year/Platform	**FundingPartner**	**Kameo**	**Monio**
2018	10.33%	12.00%	8.60%
2019	9.04%	9.30%	8.62%
2020	8.92%	9.20%	8.89%
2021	8.06%	8.36%	8.85%
2022	9.28%	8.99%	9.85%

Average loan rates - Final dataset			
Year/Platform	**FundingPartner**	**Kameo**	**Monio**
2018	N/A	N/A	N/A
2019	8.91%	10.14%	8.53%
2020	9.00%	9.11%	8.93%
2021	8.03%	8.09%	8.90%
2022	9.18%	8.96%	9.81%

4.0 Method

This section offers a detailed review of the methodology employed to compare loans across the crowdlending platforms. In addition, we will present the various bankruptcy models and econometric techniques employed in our analysis.

4.1 Bankruptcy models

We will present four bankruptcy models used throughout this thesis. Credit risk and borrowers' risk of going bankrupt is essential when dealing with loans. The lending industry is a crucial contributor to the world's financial systems. Lenders' main objective is to maximize profits, ergo minimize non-performing loans (Altman et al., 2016, p. 132). Today, numerous different bankruptcy models use both accounting and market-based information. In this thesis, we will use Altman's (1983) Z-score, Ohlson's (1980) O-score, and Zmijewski's (1984) X-score, which are all accounting-based models as all borrowers assessed are private firms. Regarding predictive accuracy, studies have shown minor differences between market-based and accounting-based models (Agarwal & Taffler, 2006, p. 24). The three different models were chosen based on two criteria: performance in prior research and that they were based on variables available in our dataset.

During the last decades, the development of bankruptcy and credit risk models has evolved considerably, with an escalating complexity aimed at assessing corporate creditworthiness. The first bankruptcy model was a single-factor model that employed key ratios to evaluate business performance. Subsequently, multiple discriminant analyses like Altman`s Z-score (1968) emerged. These innovative models were based on regression analyses, choosing variables based on their power to predict a company going bankrupt. The advancement continued with the creation of logistic and probit regression models, like Ohlson`s O-score (1980). These models incorporated dummy variables into regressions and processed them through logit and probit functions to yield a comprehensive result. The resulting scores, confined between 0 and 1, denoted the probability of a company going bankrupt. In the most recent years, advanced models such as Neural Networks and Genetic Algorithms have been crafted for the purpose of assessing corporate credit risk (F. Kinserdal, Personal communication, 2023). The forthcoming section of this thesis will offer a detailed exposition of the models employed in this research.

Grice & Dugan (2001) suggests that several bankruptcy models are experiencing a loss of predictive accuracy as time passes. Bankruptcy models seem more helpful in identifying financial distress, and Grice & Dugan (2003) suggest that researchers should use models as proxies for financial health instead of bankruptcy. Re-estimating models have improved predictive accuracy based on samples closer to the test period.

4.1.1 Altman's Z-Score

Altman's Z-Score is one of the most applied and well-known bankruptcy models. It has become a valuable tool for banks, investors, asset managers, and rating agencies (Altman et al., 2016, p. 132). The original Z-score model was developed using a sample of 66 US manufacturing firms divided into two groups. Group 1 consisted of firms that filed for bankruptcy from 1946-1965, with a mean asset size of $6.4 million. The second group consisted of a paired sample of manufacturing firms chosen on a stratified random basis based on industry and size still in existence in 1966. This group’s asset size ranged between $1-25 million. Small firms below $1 million in market capitalization were eliminated due to a lack of data, and big firms above $25 million in market capitalization rarely went bankrupt and therefore were also eliminated. As a result, the mean asset size in group 2 was slightly larger (Altman, 1968, p. 593). The model’s ability to assign each firm to its respective groups was estimated to have an accuracy of 95% (Altman, 1968, p. 609).

In 1983 the model was re-estimated and named Altman Z-Score. The model was developed for private and publicly listed firms, including manufacturing and non-manufacturing firms (Altman et al., 2016, p. 136). Four variables containing profitability, liquidity, and leverage information were included in the model. Moreover, the model classifies firms into three “zones”: safe, grey, and distressed. If a company gets a score above 2.6, it is classified as safe, while a score below 1.1 is classified as distressed. Finally, a score between 2.6 and 1.1 is classified as grey, and the company’s financial health is uncertain (Cindik & Armutulu, 2021).

The equation below explains the revised version of Altman's Z-Score (1983):

$$Z = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

Net liquid Assets:

$$X_1 = \frac{Working\ Capital}{Total\ Assets}$$

Earned Surplus:

$$X_2 = \frac{Retained\ Earnings}{Total\ Assets}$$

Profitability of assets:

$$X_3 = \frac{EBIT}{Total\ Assets}$$

Leverage Ratio:

$$X_4 = \frac{Book\ Value\ of\ Equity}{Book\ Value\ of\ total\ liabilities}$$

Equation 4.1: Altman's (1983) Z-Score.

4.1.2 Ohlson's O-Score

Ohlson (1980) gathered data from 105 bankrupt and 2058 nonbankrupt firms from 1970 to 1976. All firms had been traded on some stock exchange or over-the-counter market and classified as industrial. The period and size-factor were chosen due to practicality, being the most recent period and being able to collect financial statements (Ohlson, 1980, p. 114). Ohlson justified using only the industrial classification to exclude firms that are structurally different. Compared to other studies, Ohlson (1980) includes timing issues regarding if firms entered bankruptcy before or after the release date of financial statements. Similar to Altman`s Z-score, this bankruptcy model uses variables such as net liquid assets, debt ratios and profitability. It also introduces new variables of size, short-term debt ratio, net income change, and dummy variables for profitability and capital structure.

The initial findings in Ohlson`s (1980) study were four basic factors affecting the probability of failure within one year were statistically significant: The size of the firm, measure(s) of the financial structure, measure(s) of performance, and a measure of current liquidity. Furthermore, Ohlson stressed that the predictive power of previous studies had been overstated due to including financial statements released after the date of bankruptcy (Grice & Dugan, 2003).

Grice and Dugan (2003) proved the original model to be sensitive to industry classifications and unstable over time. Therefore, they conducted a re-estimation of Ohlson`s O-score. The re-estimated model is not sensitive to industry classifications, and their predictive accuracies are higher than the original model, justifying using the revised model in our thesis:

$$Y = -1.3 - 0.777X_1 + 3.224X_2 - 0.323X_3 + 0.589X_4 + 0.041X_5 - 2.810X_6 - 2.854X_7 + 0.372X_8 + 0.206X_9$$

Size:

$$X_1 = \log\left(\frac{Total\ Assets}{GNP - Price\ Index}\right)$$

Debt-to-asset ratio:

$$X_2 = \frac{Total\ Liabilities}{Total\ Assets}$$

Net Liquid Assets:

$$X_3 = \frac{Working\ Capital}{Total\ Assets}$$

Short term-debt-to-asset ratio:

$$X_4 = \frac{Current\ Liabilities}{Current\ Assets}$$

Dummy variable for capital structure:

$$X_5 = 1\ if\ Total\ Liabilities > Total\ Assets,\ \ 0\ otherwise$$

Profitability of assets:

$$X_6 = \frac{Net\ Income}{Total\ Assets}$$

Operations-to-liabilities ratio:

$$X_7 = \frac{Funds\ from\ Operations}{Total\ Liabilities}$$

Dummy variable for negative net income the last two years:

$$X_8 = 1\ if\ Net\ Income < 0\ for\ t\ \&\ t-1,\quad 0\ otherwise$$

Ratio for Net Income change:

$$X_9 = \frac{Net\ Income_t - Net\ Income_{t-1}}{|Net\ Income_t| + |Net\ Income_{t-1}|}$$

Equation 4.2: Ohlson's (1980) O-Score.

By running the O-score through a logit function we will get the firm's probability of going bankrupt within a year.

$$Probability\ of\ default = \frac{e^{O-score}}{1 + e^{O-score}}$$

4.1.3 Zmijewski's X-Score

Zmijewski (1984) gathered data from a population of all listed firms on the American Stock Exchange and NSE from 1972-1978. The size of the population varied between 2082 to 2241 each year. 129 firms were identified as bankrupt, with 81 observations containing sufficient data to estimate the model (Zmijewski, 1984). Listing period and financial statement data were needed to estimate the X-score model. Approximately one-third of the firms were excluded due to not meeting the size criteria necessary to have financial statements collected by Compustat (Zmijewski, 1984, p. 64). The population is firms with industry codes below 6000 (Zmijewski, 1984). This excludes financial institutions, insurance, real estate, service industry, and public administration (SEC, 2023).

Due to their performance in prior studies, Zmijewski`s model used firm performance, leverage, and liquidity as financial ratios (Grice & Dugan, 2003). However, as for Ohlson's O-score, the predictive power of Zmijewski`s X-score has decreased over time. Therefore, Grice and Dugan (2003) re-estimated the coefficients to improve predictive accuracy. They also included non-industrial companies in their re-estimated model.

$$X - score = -4.3 - 4.341X_1 + 2.106X_2 - 0.092X_3$$

<u>Profitability of assets:</u>

$$X_1 = \frac{Net\ Income}{Total\ Assets}$$

<u>Debt-to-asset ratio:</u>

$$X_2 = \frac{Total\ Debt}{Total\ Assets}$$

<u>Liquidity:</u>

$$X_3 = \frac{Current\ Assets}{Current\ Liabilities}$$

Equation 4.3: Zmijewski's (1984) X-Score. Re-estimated by Grice and Dugan (2003).

The company is defined as safe if the X-score is negative, and distressed if the score is positive (Ramdani, 2020; Zmijewski, 1984).

4.2 Econometric techniques

We will in this section present the econometric techniques used in our thesis. Firstly, we will explain how we used winsorizing to handle outlier values before describing the Mann-Whitney U test we deployed to explore differences in credit risk across the crowdlending platforms.

4.2.1 Winsorizing

Due to the limited size of the dataset, the mean and variance of the bankruptcy prediction models are sensitive to outliers. We use winsorization to reduce the impact of potential outliers. Finance frequently uses this technique to handle outlier values (Adams et al., 2019). By utilizing winsorization, all outlier values are adjusted up or down to a specified percentile, adjusting extreme values at both ends of the scale. In this thesis, we have used a 5% winsorization. As a result, all values below the 2.5th percentile are set equal to the 2.5th percentile, and all values above the 97.5th percentile are set equal to the 97.5th percentile. This type of data handling also introduces some biases but is, in most cases, a better fit than trimming (Bollinger & Chandra, 2005). Due to potential biases, all results will be presented before and after applied winsorization.

4.2.2 Mann-Whitney U test

To test if there are significant differences between loan credit scores across all platforms, we used the Mann-Whitney U test, a nonparametric alternative to the parametric t-test. This test is used to determine if there are significant differences in the median between two groups on a single ordinal variable without requiring a specific distribution (McKnight & Najab, 2010). A P-value equal to or below 0.05 indicates a significant difference. The test can also be used on samples of different sizes (Mann & Whitney, 1947). We have opted to use this test due to the non-normal distribution of credit scores and different data sizes across the platforms. Due to the model's interpretation of the scores, we test for two different tails of the distribution. A high score for Altman (1983) and a low score for Ohlson (1980) and Zmijewski (1984) indicates high credit quality.

5.0 Empirical results and discussion

This section presents the empirical results and subsequent discussions of our analysis of the differences in loan risk and characteristics across the crowdlending platforms. Section 5.1 describes mean loan sizes and terms across the platforms. Section 5.2 presents results from the bankruptcy scores and tests for significant differences. We also delve into the disparities in credit classification and the distribution of safe and distressed borrowers across platforms. In section 5.3, we analyze differences across the platforms, examining the distributions of Proff Forvalt credit classifications and the classification set by the platforms. Additionally, we investigate the differences in credit risk based on the platforms' risk classifications and the varying collateral borrowers offer. We will also explore the development of interest rates offered by the platforms. Lastly, we will analyze the actual default rates of the loans and compare them to the results from our earlier findings.

5.1 Mean loan size and average term by risk classification

FundingPartner had a stable average loan size ranging from approximately 3.3 million to 3.8 million NOK. Kameo had the largest average loan size in all year, except for 2022, where the average loan size was 3.4 million NOK. From 2019 to 2021, Kameo only issued loans above 1 million NOK. In 2022, they also issued loans below 1 million NOK. Monio has a considerably lower average loan size than its peers, almost 40% lower average loan size than FundingPartner in the studied period. FundingPartner's loan size has varied from 0.5 million to 25 million NOK, Kameo has issued loans between 0.4 million and 11.5 million NOK, and Monio between 0.3 million to 9.5 million NOK.

Figure 5.1 portrays the distribution of loan amounts from 2019 to 2022. A mere three loans exceeding 7.5 million NOK were granted in 2019 and 2020, two of which were sanctioned by FundingPartner. Moreover, in the recent past, FundingPartner has handed out a considerable number of loans that surpass the value of 7.5 million NOK. In 2021 and 2022, they issued 19 loans with a minimum value of 7.5 million NOK, hence making them the platform that issued the highest number of high-value loans.

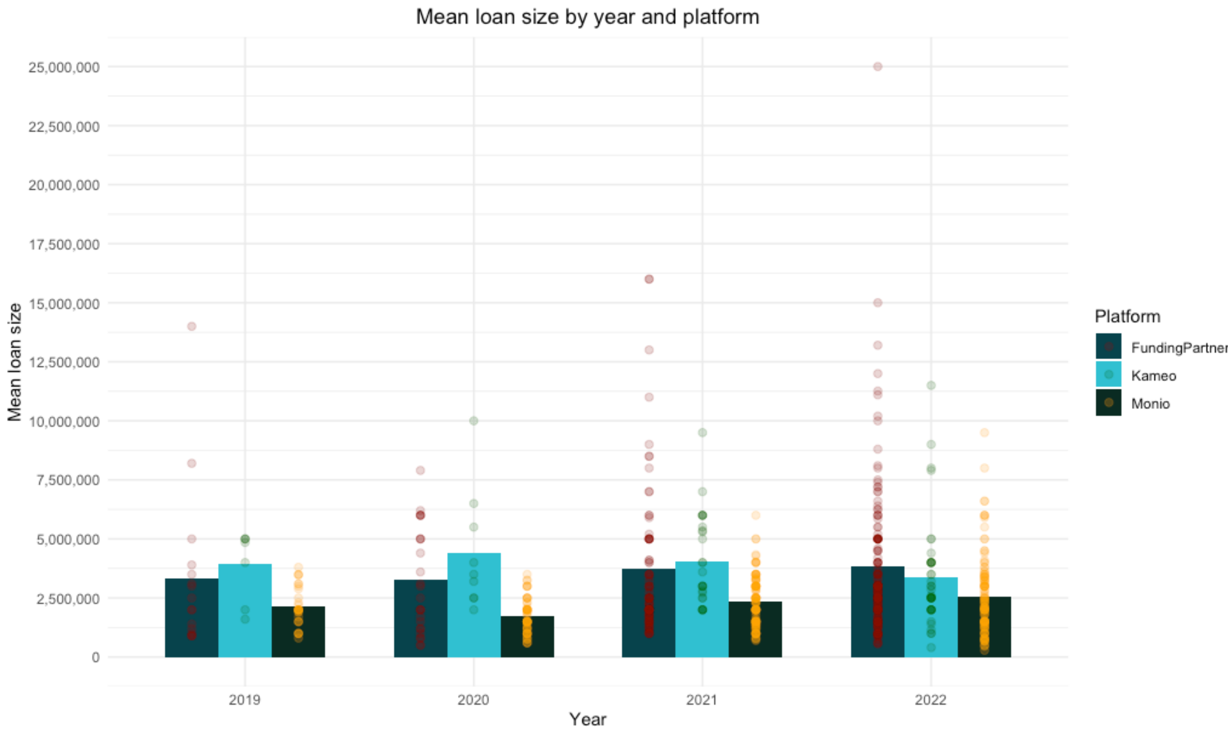

Figure 5.1: Mean loan size and distribution of loan sizes grouped by year and platform.

Larger loan sizes indicate larger projects. According to a framework developed by the University of Waterloo (n.d), larger projects often involve higher levels of complexity, longer timeframes and greater resource requirements. These factors can contribute to increased risks, for example, construction delays, cost overruns and operational challenges. However, the loan sizes are grouped by each issued loan, not by project. A project can therefore have multiple loans. Projects with multiple small loans can therefore be as complex as those with only one large loan. It is, therefore, not possible to state that high-value loans issued by FundingPartner have higher exposure to these types of risks compared to their peers.

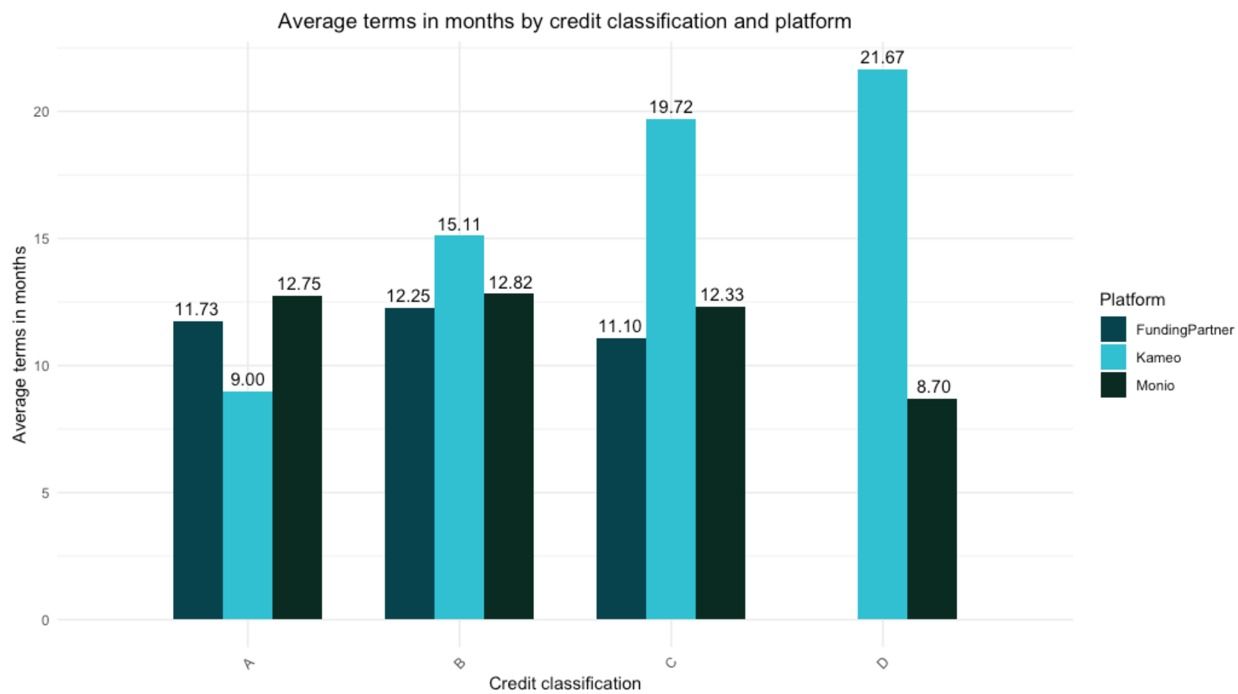

Figure 5.2: Average loan term by risk classification and platform.

Figure 5.2 presents the average loan terms in months grouped by credit classification. FundingPartner's and Monio's average term is stable at 12 months across all risk classifications, except for credit classification D. Conversely, we can see a distinct pattern between loan term and risk classification for loans issued by Kameo. Kameo has substantially longer terms on loans with credit classifications C and D than its peers, with an equally substantially shorter term on A-classified loans.

5.2 Bankruptcy model scores

The table below presents the bankruptcy models' mean and median scores before and after winsorizing the sample. This section discusses and presents the interpretation of the results obtained.

Table 5.1: Overview of the bankruptcy models' mean and median scores. Standard deviation and sample range are indicated in parentheses and brackets, respectively.

Bankruptcy model scores

Model	FundingPartner		Kameo		Monio	
	Untreated	**Winsorzed**	**Untreated**	**Winsorzed**	**Untreated**	**Winsorzed**
Altman (1983) Z-Score						
Mean (SD)	5.069 (9.903)	5.910 (2.891)	6.926 (13.951)	6.151 (3.464)	7.869 (6.152)	7.234 (3.136)
Median [Min, Max]	6.062 [-124.773, 35.070]	6.062 [1.033, 12.875]	6.185 [-65.250, 51.909]	6.185 [0.381, 12.819]	7.292 [-14.326, 38.782]	7.292 [1.033, 12.875]
Ohlson (1980) O-Score						
Mean (SD)	0.249 (0.333)	0.249 (0.333)	0.333 (0.364)	0.333 (0.364)	0.137 (0.248)	0.137 (0.248)
Median [Min, Max]	0.060 [0.001, 1]	0.060 [0.001, 1]	0.139 [0,1]	0.139 [0, 1]	0.041 [0.001, 1]	0.041 [0.001, 1]
Zmijewski (1984) X-Score						
Mean (SD)	-3.332 (5.760)	-3.270 (1.836)	-2.523 (4.400)	-3.338 (1.826)	-4.329 (4.990)	-3.731 (1.947)
Median [Min, Max]	-2.638 [-50.896, 51.927]	-2.638 [-8.936, -1404]	-3.051 [-7.904, 27.014]	-3.051 [-7.904, -1.158]	-2.937 [-28.622, 7.054]	-2.937 [-8.936, -1.404]

FundingPartner's Altman's Z-score has the lowest mean and median, both before and after winsorizing, followed by Kameo and Monio. Monio's Ohlson O-score yielded the lowest mean and median. Kameo has the highest mean and median scores for Ohlson's O-score and the highest mean for Zmijewski's X-score.

Winsorizing the sample resulted in an increased Altman's Z-score mean for FundingPartner and an improved Zmijewski's X-score mean for Kameo. Median results were unaffected for all models. Kameo's and Monio's mean Altman's Z-score was reduced. FundingPartner and Monio's Zmijewski's X-score decreased after winsorizing. The ranking remained equal to the untreated observed scores, except for Kameo having slightly better Zmijewski's X-score mean and thus passing FundingPartner in the ranks. Table 5.2 below ranks each platform according to mean and median scores based on the untreated dataset for each model.

Table 5.2: Ranking of the platforms' mean and median bankruptcy model scores, from best to worst.

Ranking of platforms based on bankruptcy score - mean and median									
	Altman Z-Score			Ohlson O-Score			Zmijewski X-Score		
	Best	**Mid**	**Worst**	**Best**	**Mid**	**Worst**	**Best**	**Mid**	**Worst**
Mean	Monio	Kameo	FundingPartner	Monio	FundingPartner	Kameo	Monio	FundingPartner	Kameo
Median	Monio	Kameo	FundingPartner	Monio	FundingPartner	Kameo	Kameo	Monio	FundingPartner

Intuitively, the bankruptcy models should be aligned, signaling which platform has the least and most probability of financial distress or bankruptcy. Monio has the best mean and median score in almost all rankings, followed by FundingPartner and Kameo. The only score where the ranking differs is the mean Zmijewski X-score, where Kameo has progressed from last to first, with Monio coming in second and FundingPartner third. By looking at borrowers overall, they are all well within the safe zone thresholds, both before and after winsorizing. Altman Z-score above 2.6 is classified as a safe zone, whereas a negative Zmijewski X-score indicates that the borrower is not in the distress zone. Lastly, Ohlson's O-score illustrates the probability of default within one year after the observation date.

5.2.1 Differences in credit classification

We conducted a Mann-Whitney U test at a 95% confidence interval to investigate significant differences in credit scores across the platform's borrowers. The first test examined whether there were general differences in bankruptcy model scores across the platforms without grouping on the platforms' credit classification. The second test grouped borrowers according to the loan credit classification. Both tests were conducted as a one-sided test. For Altman Z-score, we tested if the score is significantly greater, while we tested if the score is significantly less for Ohlson O-score and Zmijewski X-score.

Table 5.3: Mann-Whitney U test of the bankruptcy model means, with belonging W-statistics and P-value.

Mann-Whitney U Test (95% confidence)									
FundingPartner Vs Monio			FundingPartner Vs Kameo			Monio Vs Kameo			
Model	W-statistic	P-value	Model	W-statistic	P-value	Model	W-statistic	P-value	Test
Altman (1983) Z-Score	30716	1	Altman (1983) Z-Score	9947	0.6916	Altman (1983) Z-Score	15123	0.0077	Greater
Altman (1983) Z-Score Wins.	30746	1	Altman (1983) Z-Score Wins.	9935.5	0.6969	Altman (1983) Z-Score Wins.	15158	0.0069	Greater
Ohlson (1980) O-Score	49698	1	Ohlson (1980) O-Score	9302	0.0891	Ohlson (1980) O-Score	8944.5	0.0000	Less
Ohlson (1980) O-Score Wins.	49684	1	Ohlson (1980) O-Score Wins.	9256	0.0797	Ohlson (1980) O-Score Wins.	8875.5	0.0000	Less
Zmijewski (1984) X-Score	49908	1	Zmijewski (1984) X-Score	11125	0.8527	Zmijewski (1984) X-Score	11102	0.0275	Less
Zmijewski (1984) X-Score Wins.	49940	1	Zmijewski (1984) X-Score Wins.	11142	0.8576	Zmijewski (1984) X-Score Wins.	11134	0.0298	Less

Table 5.3 presents the results of the Mann-Whitney U test of the overall bankruptcy model scores. First, we assessed whether FundingPartner had significantly better credit scores than Monio. All tests returned a P-value of 1 across all models indicating the contrary; borrowers by Monio have a significantly better credit score than FundingPartner. The second pair we tested was FundingPartner and Kameo, where the obtained P-value obtained indicates no significant differences in bankruptcy model scores. Finally, we examined the scores of Monio and Kameo and discovered that Monio had significantly better credit scores across all bankruptcy models.

The results from these tests are consistent with what we experienced in Table 5.1 and 5.2. It indicates that Monio's borrowers have the best overall bankruptcy model scores compared to borrowers at FundingPartner and Kameo. There is no significant difference in credit scores between FundingPartner and Kameo.

5.2.2 Distribution of safe and distressed firms

The bankruptcy models of Altman (1983), Ohlson (1980), and Zmijewski (1984) give insight into the financial health of borrowers on different platforms. In addition, to examine the overall mean and median scores, we studied the distribution of safe and distressed borrowers across the platforms.

Table 5.4: Distribution of financially safe and distressed borrowers across the platforms.

Distribution of safe and distressed firms

Platform / Grade	Altman (1983) Z-Score			Ohlson (1980) O-Score		Zmijewski (1984) X-Score	
	Safe Zone	Grey Zone	Distress Zone	Safe Zone	Distress Zone	Safe Zone	Distress Zone
FundingPartner	87.1%	5.9%	7.1%	83.5%	16.5%	97.3%	2.7%
Kameo	88.9%	2.5%	8.6%	74.1%	25.9%	91.4%	8.6%
Monio	93.1%	3.1%	3.8%	91.5%	8.5%	98.1%	1.9%

FundingPartner has twice the share of borrowers in Altman's Z-score distress zone compared to Monio. Altman's Z-score is the only model that separates borrowers into a third category, the "grey zone". Ohlson's O-score and Zmijewski's X-score separate the borrowers into "safe zone" and "distressed zone". The ranking is equal for all bankruptcy models. Kameo has the largest share of borrowers in the distress zone, followed by FundingPartner and Monio. Monio is the only platform with over 90% of its borrowers in the safe zone for all three bankruptcy models. Grice and Dugan (2003) argued that bankruptcy models better fit as a proxy for financial distress rather than for bankruptcy. This indicates that borrowers at Monio have the lowest overall risk of experiencing financial distress, followed by FundingPartner and Kameo.

Table 5.5 presents the distribution of safe and distressed borrowers across the platform's credit classification. Intuitively, it should be the largest share of safe borrowers within A-classified loans, followed by B-, C- and D-classified loans. FundingPartner has this ranking for Altman's Z-score and Ohlson's O-score but the opposite distribution ranking for Zmijewski's X-score. Nevertheless, most FundingPartner borrowers are within the Zmijewski X-score safe zone. Kameo has a similar pattern; Altman's Z-score has a decreasing share of safe borrowers from the A to C-classification. Surprisingly, all D-classified Kameo borrowers are distributed in the safe zones of the bankruptcy models. Kameo's A-classified borrowers have a 50/50 distribution of safe and distressed zones for

Ohlson O-score and Zmijewski X-score. The share of B-classified borrowers in the safe zone is high for Altman Z-score and Zmijewski X-score but remarkably low for Ohlson's O-score. Kameo's C-classified borrowers are approximately equally distributed across all bankruptcy models. Lastly, Monio's distribution across credit classification is consistent with the expectation of distributions. The distribution of B-classified borrowers is slightly worse than for C-classified borrowers across all bankruptcy models. Generally, most borrowers at Monio are within the safe zone for all credit classifications and bankruptcy models.

Table 5.5: Distribution of financially safe and distressed borrowers across the platforms' credit classifications.

Distribution of safe and distressed borrowers by credit classification

Platform / Grade	Altman (1983) Z-Score			Ohlson (1980) O-Score		Zmijewski (1984) X-Score	
	Safe Zone	Grey Zone	Distress Zone	Safe Zone	Distress Zone	Safe Zone	Distress Zone
FundingPartner							
A	93.3%	3.3%	3.3%	93.3%	6.7%	96.7%	3.3%
B	87.1%	6.2%	6.7%	83.5%	16.5%	96.9%	3.1%
C	80.6%	6.5%	12.9%	74.2%	25.8%	100%	0%
Kameo							
A	100%	0%	0%	50.0%	50.0%	50.0%	50.0%
B	92.1%	5.3%	2.6%	60.5%	39.5%	97.4%	2.6%
C	81.2%	0%	18.8%	84.4%	15.6%	84.4%	15.6%
D	100%	0%	0%	100%	0%	100%	0%
Monio							
A	100%	0%	0%	100%	0%	100%	0%
B	91.8%	3.7%	4.5%	88.8%	11.2%	98.5%	1.5%
C	94.0%	3.0%	3.0%	93.4%	6.6%	98.2%	1.8%
D	90.0%	0%	10.0%	90.0%	10.0%	90.0%	10.0%

Table 5.5 suggests that the distribution of credit classifications for borrowers at FundingPartner and Monio is mostly consistent with the intuition of the bankruptcy models. Intuitively, there should be less financially safe borrowers with B-classified loans than A, and less financially safe borrowers with C-classified loans than B etc. Monio seems to have less risky borrowers than the other two platforms for most credit classifications. This aligns with the results from the overall distribution of borrowers across the platforms, illustrated in Table 5.4. Kameo had contrary results for A- and D-classified borrowers. These results suggest that borrowers at Kameo have riskier A-classified loans than D-classified. Only two and nine borrowers at Kameo are A- and D-classified, respectively. The small sample size makes the result of Kameo's distribution of A- and D-classified borrowers less credible. It is worth noting that the ranking of platforms remain equal, with Monio having the least risky borrowers based on the distribution of safe and distressed firms. In the next section, we will test if there are significant differences in credit classification across the platforms.

5.2.3 Differences within platforms' credit classification

Table 5.6 presents the Mann-Whitney U test results on the bankruptcy model scores, grouped by the platform's credit classification. The test is conducted with 95% confidence, revealing significant differences in bankruptcy scores across the platforms. As mentioned in section 4.3.2, we tested if Altman's Z-score is significantly *greater* for one platform versus the other. We tested whether the scores were significantly *lower* for Ohlson's O-score and Zmijewski's X-score. This decision was made to get a uniform and interpretable result.

Firstly, we tested if FundingPartner has a significantly better credit score than Monio. Testing Zmijewski's X-score indicated that Monio has significantly better credit scores for A-classified loans. Testing Altman Z-score and Ohlson O-score did not return any significant differences. All tests for B-classified loans indicate significantly better bankruptcy model scores for Monio versus FundingPartner. There were no significant differences for C-classified loans.

Comparing test results for FundingPartner versus Kameo reveals that Kameo has a significantly better Altman Z-score than FundingPartner for A-classified loans. Ohlson's O-score, on the other hand, indicates the opposite. No significant difference is found when testing Zmijewski X-Score for A-classified loans. Also, no significant differences are found in testing Altman's Z-score or Ohlson's O-score for B-Classified loans. However, test results from Zmijewski's X-Score indicate that Kameo has a significantly better score than FundingPartner for B-classified loans. FundingPartner has a significantly better Altman Z-Score and Zmijewski X-Score for C-classified than Kameo. No significant difference is found when testing Ohlson's O-score for FundingPartner versus Kameo's C-classified loans.

Finally, we test Monio's borrowers versus Kameo's. Due to the small sample size for A-classified loans for Kameo and Monio, the tests conducted on this classification have reduced credibility. The test indicated that, for B-classified loans, Monio has significantly better Ohlson's O-score than Kameo. At the same time, testing Altman Z-score and Zmijewski X-score yielded no significant difference. Testing for C-classified loans indicates better scores for Monio's borrowers across all bankruptcy models. For D-classified loans, on the other hand, Kameo has significantly better credit scores across all bankruptcy models, indicating less risky borrowers compared to Monio.

Table 5.6: Mann-Whitney U test statistics and P-value for the bankruptcy model scores across FundingPartner, Kameo and Monio. The test is conducted on the platform's borrowers and grouped by respective loans credit classification.

Mann-Whitney U Test (95% confidence)

Credit classification ->	A		B		C		D		
Model	**W-statistic**	**P-value**	**W-statistic**	**P-value**	**W-statistic**	**P-value**	**W-statistic**	**P-value**	**Test**
FundingPartner Vs Monio									
Altman (1983) Z-Score	90	0.8630	10072	0.9997	2126	0.9378			Greater
Altman (1983) Z-Score Winsorized	90	0.8631	10076	0.9997	2124	0.9387			Greater
Ohlson (1980) O-Score	137	0.7348	16210	0.9999	2929	0.8896			Less
Ohlson (1980) O-Score Winsorized	138	0.7465	16212	0.9999	2920.5	0.8840			Less
Zmijewski (1984) X-Score	180	0.9850	15642	0.9991	2832	0.8136			Less
Zmijewski (1984) X-Score Winsorized	180	0.9850	15598	0.9990	2883.5	0.8574			Less
FundingPartner Vs Kameo									
Altman (1983) Z-Score	7.5	0.9637	3342	0.8188	648.5	0.0182			Greater
Altman (1983) Z-Score Winsorized	8.5	0.9571	3345.5	0.8164	636.5	0.0268			Greater
Ohlson (1980) O-Score	5.5	0.0305	3110.5	0.0642	386.5	0.0668			Less
Ohlson (1980) O-Score Winsorized	5	0.0279	3119	0.0670	376.5	0.0506			Less
Zmijewski (1984) X-Score	18.5	0.1953	4596	0.9920	328.5	0.0107			Less
Zmijewski (1984) X-Score Winsorized	20	0.2290	4600	0.9922	331	0.0118			Less
Monio Vs Kameo									
Altman (1983) Z-Score	2	0.9581	2768	0.2066	3993	0.0000	12	0.9971	Greater
Altman (1983) Z-Score Winsorized	3	0.9302	2785	0.1891	3978	0.0000	12	0.9971	Greater
Ohlson (1980) O-Score	0	0.0230	1655.5	0.0005	1414	0.0000	77	0.9963	Less
Ohlson (1980) O-Score Winsorized	0	0.0230	1631	0.0004	1404	0.0000	77	0.9963	Less
Zmijewski (1984) X-Score	0	0.0230	2498	0.4304	1333	0.0000	69	0.9782	Less
Zmijewski (1984) X-Score Winsorized	0	0.0230	2501	0.4347	1345.5	0.0000	69	0.9782	Less

The findings suggest the following ranking of credit risk for borrowers with A-classified loans: Monio, FundingPartner and lastly, Kameo. However, as mentioned, these results should be treated with somewhat caution due to the small dataset of A-classified loans for both Monio and Kameo. For B-classified loans, the pattern is consistent with the A-classified loans. Specifically, Monio hosts the least risky borrowers within the B-classification, this time followed by Kameo and, lastly, FundingPartner. Among C-classified loans, the test displays that both FundingPartner's and Monio's borrowers have significantly better bankruptcy model scores than Kameo. However, no significant disparities are detected between FundingPartner and Monio, effectively placing Kameo as the platform hosting the riskiest C-classified borrowers. Paradoxically, when analyzing D-classified loans, Kameo's borrowers exhibit significantly better bankruptcy model scores than Monio. This observation implies that Monio, despite exhibiting stronger performance in higher credit classifications, might host some of the riskiest borrowers across all platforms, evidenced by their lowest bankruptcy model scores within the D-classified loans.

Balyuk & Davydenko (2023) explained that crowdlending has evolved from removing intermediaries to becoming the intermediate themselves. They argued that investors have shown confidence in crowdlending platforms to conduct thorough analyses and assign accurate credit classifications. Recent media development displays the importance of trust, where Monio especially struggles with the aftermath of the public critique. FundingPartner and Kameo are also experiencing the side effect of the public possible loss of trust in the platforms. The arguments used by the various parties participating in the public discussions underline Balyuk & Davydenko's (2023) view, where the perception seems that crowdlending parties' operating area goes beyond matching borrowers with lenders. However, it should be noted that the platform's incentive is to boost transaction volume, hence also their fees. Consequently, the credit classification platforms provide may be influenced by the lenders' high demand for investing in loans rather than accurately reflecting the borrower's actual credit quality. This potential deviation might account for the significant disparities observed in credit scores across the various credit classifications allocated by the platforms. Nevertheless, as highlighted by Klafft (2008), it may exemplify the incentive structure that makes information asymmetry issues.

5.3 Distribution of credit classifications across the platforms

This subchapter explores further differences across crowdlending platforms. Firstly, we present the platform's distribution of Proff Forvalt's credit classifications. Furthermore, we describe the distribution of credit classifications set by the platforms. Additionally, we analyze the collateral, and interest rates set by the platforms.

5.3.1 Share of observations for each Proff Forvalt classification by platform

Proff Forvalt (2023) provides credit classification and credit scores for companies with adequate accounting information. The classification is determined by examining financial statements, shareholders, key organizational roles, board information, collateral, and payment records. The rating system assigns companies A++, A+, A, B, or C classification with corresponding bankruptcy rates of 0.00, 0.09, 0.22, 1.13, and 6.83% (Proff Forvalt, 2023).

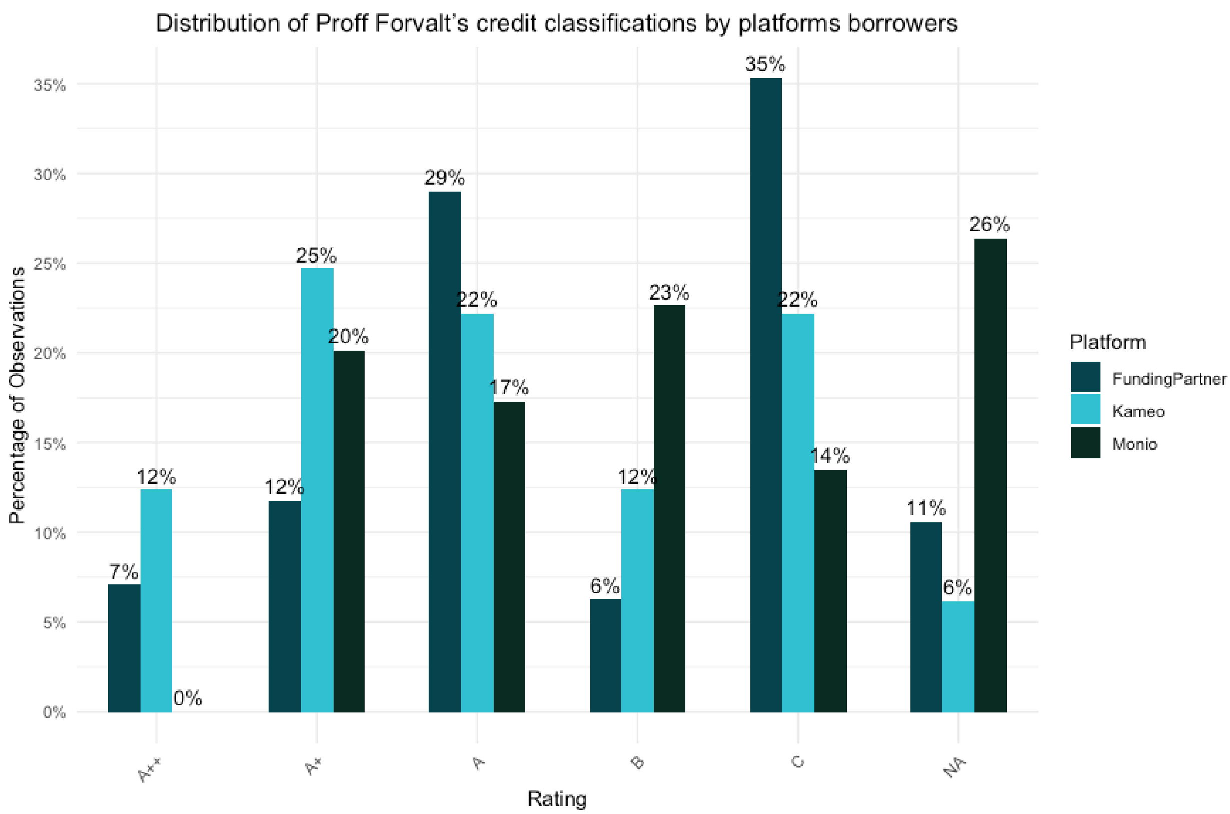

Figure 5.3: Distribution of borrowers across Proff Forvalt's credit classification, grouped by platform and Proff Forvalt's credit classification.

48% of FundingPartner's borrowers are classified as A or above. For Kameo and Monio, this share is 59% and 37%, respectively. When looking at borrowers that are B-classified FundingPartner has the smallest proportion with only 6%, followed by Kameo and, lastly, Monio with the largest share of 23%. A total of 35% of FundingPartner's borrowers are C-classified. Kameo has a total of 22%, and Monio has the lowest share, with only 14% C-classified. Finally, FundingPartner, Kameo and Monio have 11%, 6%, and 26% non-observable observations, respectively. The reason for non-observable observations can be a lack of necessary input data to compute the classification.

The results from the distribution of the scores above imply that Monio has the fewest top-rated borrowers compared to Kameo and FundingPartner. This contradicts the results from the bankruptcy model scores. At the same time, we clearly see a difference in the share of C-classified borrowers. Monio has a notably lower share of C-classified borrowers than FundingPartner and Kameo. This supports our findings from the bankruptcy models. Large proportions of C-classified borrowers from FundingPartner and Kameo might affect the mean and median scores, as presented in Tables 5.1 and 5.2. The results are sensible when looking at the classifications corresponding bankruptcy rates of 0.00, 0.09, 0.22, 1.13, and 6.83%. When calculating a weighted average considering the distribution and bankruptcy rates for each classification, the anticipated default rates for FundingPartner, Kameo, and Monio stand at 2.53%, 1.71%, and 1.27%, respectively. C-classified borrowers have the most distinguished bankruptcy rates, six times more frequent than B-classified borrowers. Proff Forvalt's credit classification is not a sufficient measure of credit quality on its own. Nevertheless, analyzing the unbiased distribution of credit classification provided by Proff Forvalt may shed light on the creditworthiness of borrowers on each platform, providing the foundation for further investigation into potential differences in their borrower classifications. Next, we will explore the distribution of credit classification set by the platforms.

5.3.2 Distribution of the platforms' credit classification

Figure 5.4 illustrates FundingPartner's loans are mostly B-classified, amounting to 76%. The remaining 24% is equally distributed between A and C-classified loans. FundingPartner is the platform with the largest share of A-classified loans compared to its peers. As mentioned earlier, FundingPartner have not yet issued D-classified loans. Kameo and Monio have quite equal distributions of classifications. They have similar portions of A-classified loans with 2% and 3%, respectively. The proportions are 47% and 42% for B-classified loans, respectively. Monio has a larger proportion of C-classified loans compared to Kameo. On the other hand, Kameo has the largest proportions of D-classified loans.

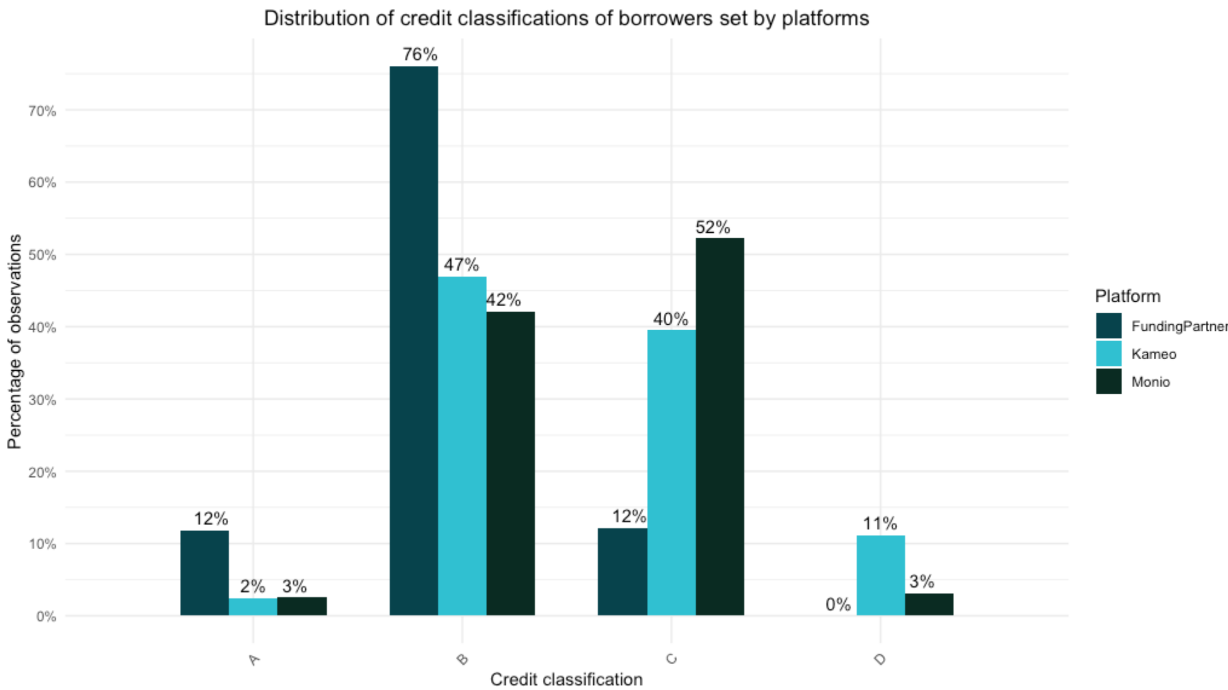

Figure 5.4: Distribution of borrowers across the platform's credit classification, grouped by platform and credit classification.

FundingPartner classified 88% of their loans as either A or B, while Kameo and Monio classified 49% and 45% of their loans as either A or B. The platform's own credit classification indicated that FundingPartner issued the loans with the lowest credit risk, contradicting the bankruptcy model results. Both our bankruptcy models and Proff Forvalt's credit classification indicated that FundingPartner was not the platform with the lowest overall credit risk. It is also interesting that only 12% of the loans issued from FundingPartner got their lowest classification, in contrast to Proff Forvalt's credit classification, where a total of 35% of borrowers got the lowest classification. Kameo had the second largest portion of their loans classified as either A or B, and the second largest portion for C- and D-classified at 51%. Monio had the smallest share of A- and B-classified loans and the largest proportion with C- and D-classified at 55%, contrary to the results from the bankruptcy models where Monio had the lowest overall credit risk.

The distribution suggests internal differences in credit classification. Monio seems more cautious about classifying loans as A and B. It is important to combine these results with results from Table 5.6. Monio had the least risky borrowers for both A- and B-classified loans, evident by testing the bankruptcy model scores. FundingPartner's borrowers ranked second for A-classified loans and third for B-classified loans. As mentioned above, 88% of FundingPartner's loans are either A- or B-classified, underlining the importance of understanding differences between, for example, an A-classified loan at FundingPartner versus Monio. This is crucial in understanding the presence of any biases in the loan classification system of the platform, which could have far-reaching implications for lenders' loan evaluations and decision-making.

Several reasons may explain why the results are contradictory. The Proff Forvalt credit classification and bankruptcy models are based on the borrower, not the loan. For example, the platforms incorporate project-specific risk and various forms of collateral when classifying loans. While this section provided evidence of internal differences in credit classification, it is necessary to explore if the lenders get rewarded for the risk differences of the platform's borrowers.

5.4 Project-specific risks

This section will discuss project-related risk and how it potentially differs between the platforms. Project-specific risk is not captured by the bankruptcy models, and borrowers may experience different classifications by platforms due to risk related to the funded project. First, we will complement the arguments and findings from sections 5.1 and 5.2 related to project risk factors by assessing how the platform operates regarding collateral. Lastly, we will finalize our findings by summarizing differences in the platform's credit classification by highlighting if lenders are properly rewarded for credit classification differences by looking at interest rates.

5.4.1 Distribution of collateral types

Table 5.7 summarizes each platform's share and type of collateral. Notable differences in the composition of collateral across the platforms are illustrated. Group guarantees are secured by assets, equity, or stock within the same group as the borrower firm. FundingPartner is the only platform where most loans are secured by personal guarantees that fully or partially cover the loan. Conversely, Monio and Kameo have less than 5% of their loans secured by personal guarantees. Additionally, FundingPartner has the highest share of loans secured by group guarantees from one or more firms beyond the borrowing firm. Kameo also has a substantial proportion of loans with group guarantee. In contrast, Monio has a significantly lower proportion of group-guaranteed loans. Concerning project guarantees, all platforms have a substantial portion of their loans secured by the funded projects. FundingPartner and Monio have nearly all loans guaranteed by the funded project.

Table 5.7: Distribution of collateral across FundingPartner, Kameo and Monio. Group collateral is the term used for collateral in firms beyond the borrowing firm.

Share and type of collateral for loans

Collateral/Platform	FundingPartner	Kameo	Monio
Personal	63.9%	4.9%	4,7%
Group	41.3%	34.6%	8.5%
Project	94.9%	76.5%	97.8%
Prioirity	**Loan priority for project guarantee**		
1st	67.8%	67.8%	64.3%
2nd	26.4%	30.6%	27.0%
3rd or higher	5.8%	1.6%	8.7%

The latter part of Table 5.7 offers an overview of the priority distribution for project guarantees across the platforms. Approximately 2/3 of all loans with project guarantees have the first priority for all platforms. All three platforms display comparable proportions of second-priority guarantees. Yet, Kameo significantly underrepresents loans with third or higher-priority guarantees compared to FundingPartner and Monio.

Collateral reduces moral hazard problems (Flatnes & Carter, 2019). By providing collateral, borrowers should act less riskily due to being more affected if defaulting. Loans secured by personal or group guarantees are loans subject to the least moral hazard problems, due to the borrower being substantially affected in case of default. Utilizing special purpose vehicles (SPVs), or project companies, is a typical corporate structure in the real estate sector. This approach allows the owner to compartmentalize the risk associated with each property. If one property of a project fails, the other remains unaffected, given that they are not used as collateral. In such scenarios, sufficient guarantees from firms and personal guarantees are crucial to mitigate the lenders' risk.

Monio has the fewest loans issued with personal, group guarantees and first priority project guarantees. The only category where Monio's loans are not the least secured is for third or higher project priority. Having the largest share of third or higher priority also indicates that the platform struggles to retain collaterals with higher priorities due to other credit instances having higher priorities. Consequently, lenders are exposed to more considerable risk since the collateral narrows mostly to the funded projects, compared to FundingPartner and Kameo. Contrary to Monio, FundingPartner issued 64% of all loans with a personal guarantee, and 41% of all loans were reinforced with group guarantees. Given the potential for some loans to be safeguarded by both personal and group guarantees, a minimum of 64%, and up to potentially all loans, are secured by personal or group collateral. This reduced the risk of moral hazard, transferring a considerable proportion of the risk to the borrower in the event of default. Consequently, this denotes a reduction in risk associated with FundingPartner's loans compared to, especially, Monio's.

Kameo's loans feature personal collateral for 5% and group collateral for 35% of all cases. This indicates an upper limit of approximately 40% of all loans secured by personal or group collateral. Although this is significantly superior to Monio, it is still substantially lower than FundingPartner. Conclusively, Kameo could be considered in-between its peers in relation to collateral and guarantees.

5.4.2 Interest rates

This subchapter presents the average monthly interest rates across the platforms. Figure 5.5 presents the overall average interest rate, while Figures 5.6 to 5.9 illustrate each credit classification's monthly average interest rate. Comparing the policy rate with the average loan rate allows us to study the rate gap, thereby clarifying the reward lenders collect from investing in the given loans.

Figure 5.5 illustrates a consistent trend in average loan rates throughout the observed period, despite some short-term discrepancies among the platforms. FundingPartner and Kameo display some sporadic spikes that deviate from the general trend. These deviations are due to few loans issued in the given month with a temporary dominance of high- or low-risk loans. The development from the start of 2022 illustrates the platforms' reaction to policy rate hikes and consequently increased their interest rates.

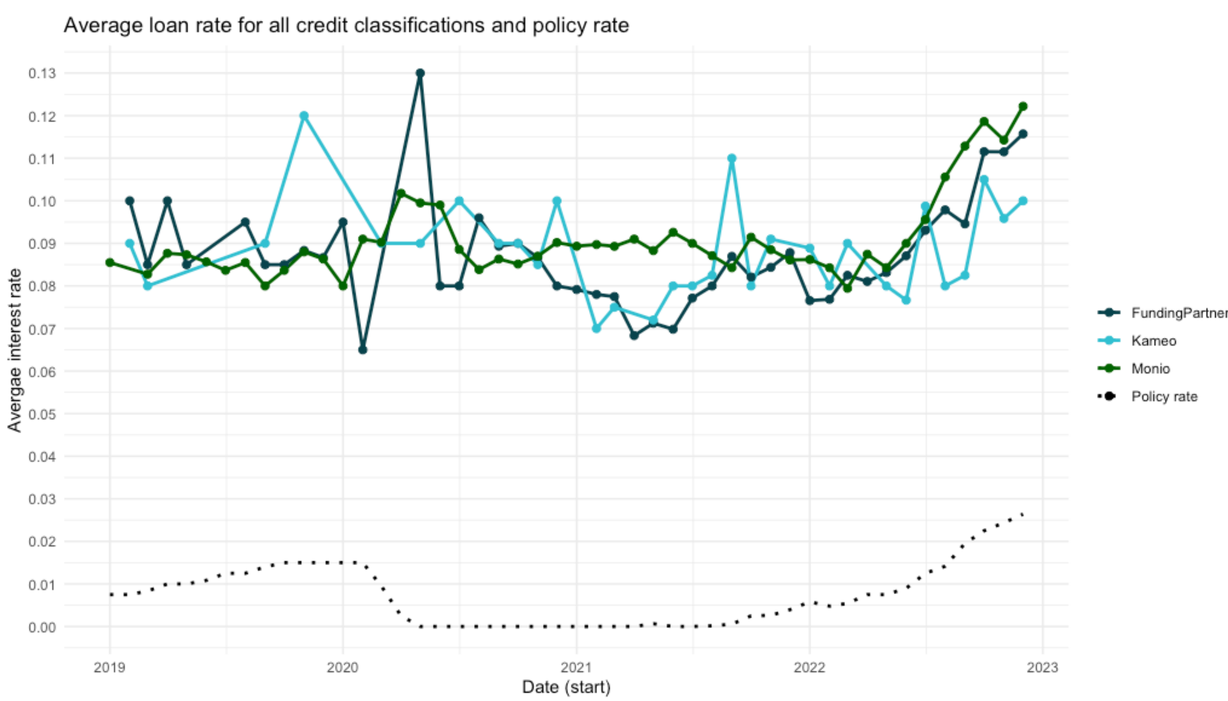

Figure 5.5: Monthly average overall interest rate. Each data point indicates the monthly average for the corresponding period, ranging from 2019 to the end of 2022. The policy rate set by the central bank of Norway is illustrated as a black dotted line. No loans were issued in the months where the figures lack data points.

As illustrated by Figure 5.6, the sample size for credit classification A is somewhat small. However, the average interest rates for both FundingPartner and Monio are stable. For instance, in the first quarter of 2021, the rate gap for FundingPartner and Kameo was approximately 6.5%, while Monio exhibited a slightly higher gap at 7%. A notable deviation occurred in the final quarter of 2022, where FundingPartner was the only platform issuing A-classified loans, following the severe interest hikes.

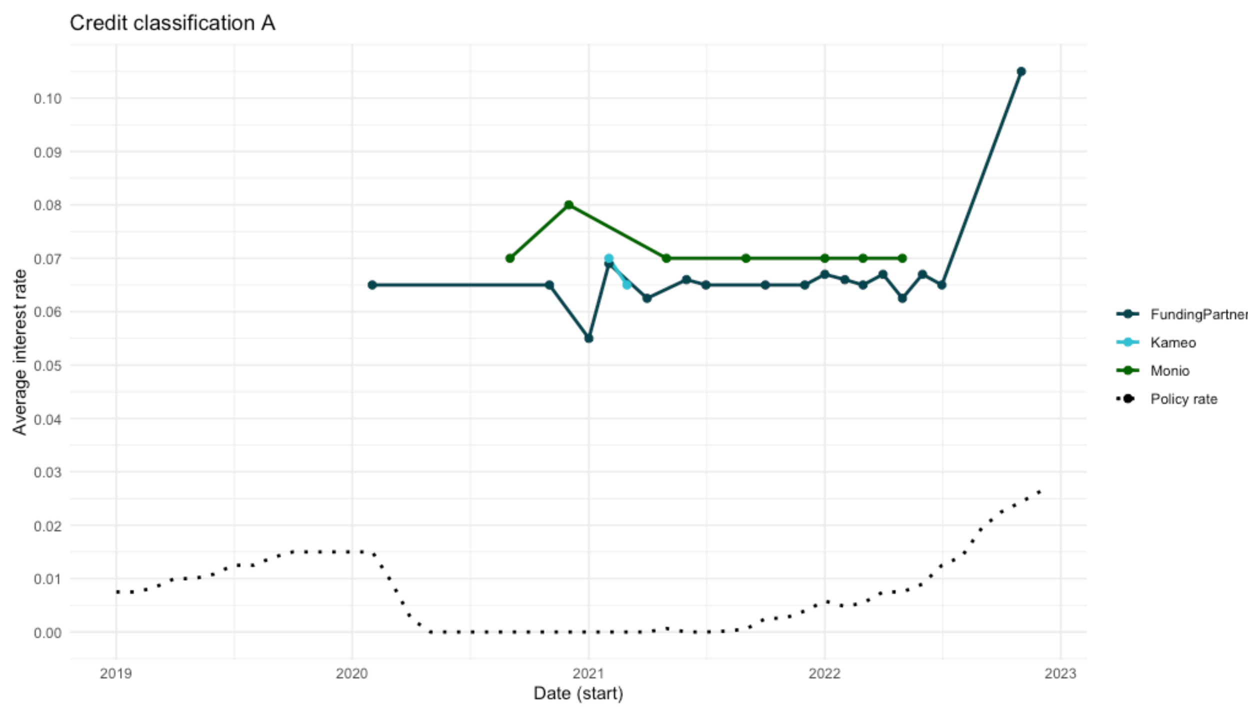

Figure 5.6: Monthly average interest rate for A-classified loans. Each data point indicates the monthly average for the corresponding period, ranging from 2019 to the end of 2022. The policy rate set by the central bank of Norway is illustrated as a black dotted line. No loans were issued in the months where the figures lack data points.

Within credit classification B, Figure 5.7 displays average interest rates similarities, with equal rate gaps. At the start of the second quarter of 2021, FundingPartner, Kameo and Monio exhibited rate gaps to the policy rates of 7%, 6.8% and 8.5%, respectively. The rate gaps changed to 9%, 7.5% and 8.3% by the end of 2022. Both FundingPartner and Kameo increased their rate gaps, while Monio reduced theirs. Another noteworthy observation is the substantial reduction in Kameo's average loan rates during the third quarter of 2022, this was caused by the issuance of two loans, with low loan rates.

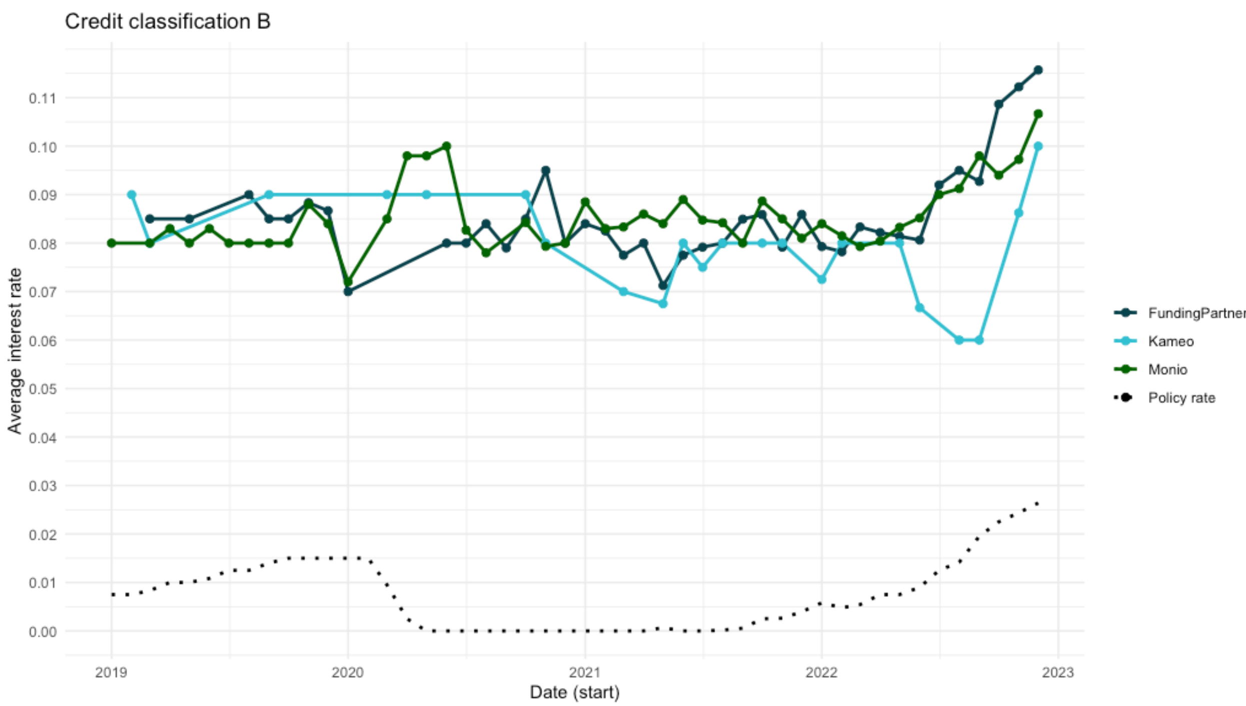

Figure 5.7: Monthly average interest rate for B-classified loans. Each data point indicates the monthly average for the corresponding period, ranging from 2019 to the end of 2022. The policy rate set by the central bank of Norway is illustrated as a black dotted line. No loans were issued in the months where the figures lack data points.

Figure 5.8 illustrates that the interest rate gaps expand for credit classification C. However, all platforms still echo the trend set by the policy rate. There was a decrease in average interest rates across all platforms during the second quarter of 2020, responsive to the decline in policy rates. During the phase of policy rates at 0%, FundingPartner had a low amount of C-rated loans. However, as policy rates ascended, FundingPartner's issuance of C-rated loans rose. Equal to the response at the beginning of 2020, the platforms loan rates follow the trend of the policy rate.

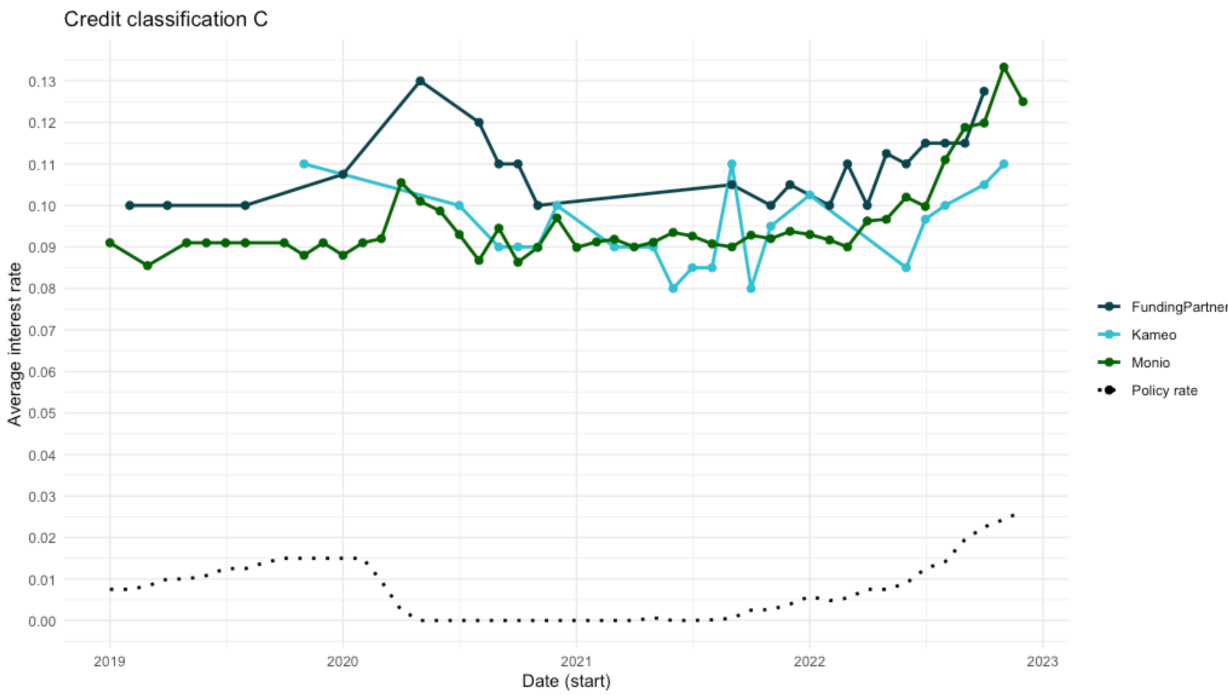

Figure 5.8: Monthly average interest rate for C-classified loans. Each data point indicates the monthly average for the corresponding period, ranging from 2019 to the end of 2022. The policy rate set by the central bank of Norway is illustrated as a black dotted line. No loans were issued in the months where the figures lack data points.

Figure 5.9 only includes Kameo and Monio due to loans with credit classification D being solely offered by the two platforms. Monio offers a higher interest rate for all monthly observations. One can identify a trend where the quantity of D classified loans rises along with the policy rate, a pattern that mirrors the development within C classified loans on the FundingPartner platform.

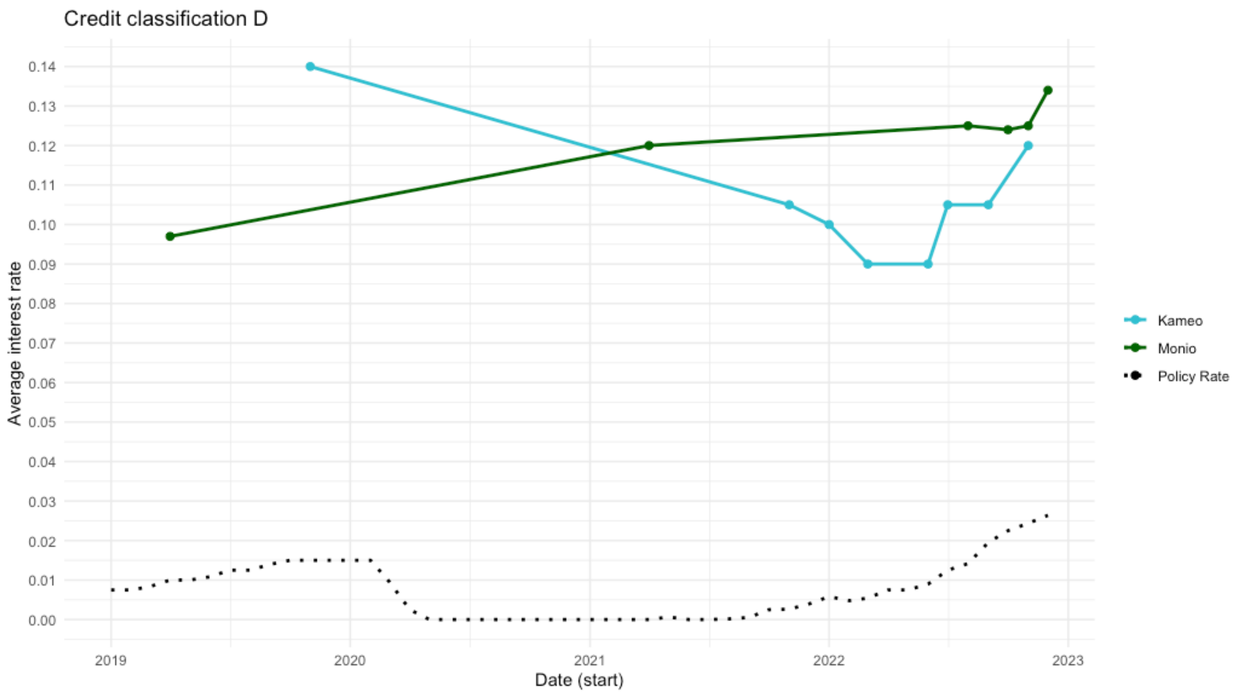

Figure 5.9: Monthly average interest rate for D-classified loans. Each data point indicates the monthly average for the corresponding period, ranging from 2019 to the end of 2022. The policy rate set by the central bank of Norway is illustrated as a black dotted line. No loans were issued in the months where the figures lack data points.

As previously addressed in Section 2.2, loan rates are determined based on a borrower's credit risk and market demand. Possible explanatory factors for the noticeable fluctuations within each credit classification may be minor changes in risk within each credit category, shifts in demand, and variations in policy rates.

As indicated in Figure 5.5, all platforms raised interest rates along with the hikes in policy rates, with only minor variations. The mean stabilizes as time passes, as each platform issues more loans per month. Credit classification A shows a stable development during the low policy rate period.

However, after the excessive hikes in policy rates, FundingPartner is the only platform to have issued an A-rated loan. As mentioned previously, FundingPartner's borrowers of A-classified loans seem riskier than Monio. Table 5.8 suggests that the lenders are not rewarded for this, evidently offered a lower interest rate than lenders investing in A-classified loans at Monio. Some of this may be explained by the operating differences regarding collateral. Nevertheless, the findings suggest differences in credit classification that may not be apparent for unsophisticated lenders. Klafft (2008) suggested that information asymmetry, as well as being inexperienced, hinder lenders' likelihood of achieving attractive returns on their investments.

The quantity of A-classified loans decreases, and the number of poorly graded loans increases with hikes in the policy rates. This may suggest that the platforms do consider hikes policy rates when both determining their credit classifications and interest rates.

Table 5.8: Average interest rates across credit classifications. No loans were issued where the table lacks average interest rates. The last row is the average interest rate per credit classification.

Average loan rates across credit classification and year

	FundingPartner			Kameo				Monio			
	A	**B**	**C**	**A**	**B**	**C**	**D**	**A**	**B**	**C**	**D**
2019	-	8.65%	10.00%	-	8.75%	11.00%	14.00%	-	8.16%	8.96%	9.70%
2020	6.50%	8.21%	11.44%	-	8.75%	9.40%	-	7.50%	8.48%	9.27%	-
2021	6.44%	8.17%	10.30%	6.75%	7.46%	8.95%	10.50%	7.00%	8.48%	9.15%	12.00%
2022	6.83%	9.22%	11.27%	-	7.61%	10.00%	10.00%	7.00%	8.65%	10.90%	12.80%
Total	6.64%	8.79%	11.03%	6.75%	7.80%	9.64%	10.50%	7.13%	8.51%	9.66%	12.41%

FundingPartner's and Monio's average B-classified interest rates align closely during the whole period except for the last observations of 2022. Table 5.8 suggests that FundingPartner's and Monio's average B-classified interest have been quite stable and equal during the four-year period. Despite this, the previous test results suggest that FundingPartner borrowers of B-classified loans are riskier than Monio's borrowers. As for A-classified loans, lenders are not rewarded for this risk. The differences may be due to factors such as collateral, but no clear guidelines, regulations or supervision provide lenders with information regarding this. Jagtiani & Lemieux (2017) argued that the lack of supervision compared to traditional banks may lead to fair lending violations. We do not suggest that there is evidence of fair lending violations, but we argue, as Mortiz & Block (2014), that further market studies are needed to assist lenders in their decision-making. Estimating default probability is challenging for researchers and crowdlending, but also for unsophisticated investors.

5.6 Actual defaults and confirmed losses

This section will provide insight into the platforms' actual defaults and their confirmed losses upon May 2023. All platforms have encountered instances of borrowers defaulting. This provides critical insight into the platforms' ability to assign accurate credit classifications.

As of May 2023, FundingPartner has experienced a total of nine borrowers defaulting out of these borrowers, five related to real estate projects. A total of 299 loans were issued to real estate projects, resulting in a total default rate of 1.67% to real estate projects. The platform is in the process of recovering funds for all five loans. At the end of Q1 2023, FundingPartner had a total of 902 million NOK in outstanding loans, where 9.3 million NOK of loans defaulted and were under active recovery. This also includes non-real estate projects. This leads to a current default rate of 1.03%. It is interesting to note that four out of these five loans were classified as B, and only one was classified as C. Considering that FundingPartner has issued 219 B-classified loans and 44 C-classified loans, the default rates for the different credit classifications turn out to be 0% for A-classified loans, 2.28% for B-classified, and 2.27% for C-classified (FundingPartner, 2023).

The Norwegian branch of Kameo has faced a total of eight loan defaults, with seven of these loans related to real estate projects of their 110 real estate loans. This equals a default rate of 6.36% to real estate projects. Of these seven loans, recovery is in process for five, amounting to a total sum under collection of 11.95 million NOK. Since Kameo does not supply data on the total value of outstanding loans, we cannot compute the present default rate in NOK. However, given that Kameo has a lower volume than FundingPartner, yet has a larger sum under collection, it suggests a higher default rate. Out of the seven defaulted real estate loans, six were rated as C, and one as B. Considering that Kameo has issued 48 C-classified loans and 47 B-classifiedloans, the default rate for each credit classification is 0% for A-classified, 2.13% for B-classified, 12.5% for C-classified and 0% for D-classified (Kameo, 2023).

Monio has a total of 24 defaulted loans from their portfolio of 381 loans, resulting in a default rate of 6.3%. This figure does not account for defaulted loans currently under collection, as Monio does not provide data on this aspect (Monio, 2023). As of May 2023, Monio has outstanding loans totaling 370 million NOK. Of this amount, just over 70 million have defaulted, resulting in a default rate of 19% (Oftebro, 2023). Of the loans with confirmed losses, two were B-classified, 15 were C-classified and seven were D-classified. Considering that Monio has issued 159 B-classified loans, 192 C-classified loans, and 16 D-classified loans, the default rate for each credit classification is 0% for A-classified, 1.26% for B-classified, 7.81% for C- and 43.75% for D-classified (Monio, 2023). These numbers do not include defaulted loans currently under collection and are therefore subject to potentially increase.

These results suggest that all platforms can correctly assign A- and B-classified loans as these risk classifications have low default rates. This is also the case for C-classified loans from FundingPartner. Default rates might indicate some classification errors at Kameo, where C-classified loans have a significantly larger share of defaults than D-classified loans. It also indicates the C-classified loans to be of high risk compared to their peers. This result aligns with the results from Table 5.6, which suggests that Monio have the riskiest borrowers with C-classified loans. Monio has also been able to assign correct credit classifications as the share of default increases from C- to D-classified loans. The default rate also suggests high credit risk for C- and D-classified loans.

6.0 Limitations

This thesis analyzes the differences between FundingPartner, Kameo, and Monio. To examine differences, we manually gathered data from the three platforms and financial statements of their real estate borrowers from 2018 to 2022. We applied methods such as computing bankruptcy scores based on the models of Altman (1983), Ohlson (1980), and Zmijewski (1984). The thesis severely depends on our dataset's quality and the choice of relevant models and methods. In addition, the size of our sample is also crucial. Factors like the quality of our data gathering are in our power to control. Other factors, like the validity of bankruptcy models in general, are outside our power to control. Nevertheless, it is essential to understand the limitations of this thesis. Thus, this section will discuss such limitations in detail. Firstly, we will explain the limitations of using financial statements for predicting bankruptcy and financial distress. Secondly, we will discuss how the lack of historical crowdlending data affects our thesis. Lastly, we will discuss how errors may occur while gathering data and the limitations a small dataset may have.

6.1 Use of financial statements in models to predict bankruptcy and financial distress

The bankruptcy models computed in this thesis solely rely on financial statements. Borrowers' financial statements are retrieved from the year before the loan is issued. Theoretically, the loan could be issued in late December, making the financial statements less valid as a foundation for the analysis than if they were posted at the start of the year. Financial statements retrieved from only one period do not reflect qualitative factors such as management, owners' motivation for avoiding bankruptcy, industry-, economic- and macroeconomic developments.

Altman`s, Ohlson`s, and Zmijewski`s bankruptcy models are all well-known within financial literature. The models have proven to predict bankruptcy accurately across different markets and countries (Bellovary et al., 2007; Balcaen & Ooghe, 2006). However, due to country-specific laws, the sample bankruptcy model scores are based on might vary. For example, only large corporations must publish their annual accounting information in countries such as the US, the UK and Germany (Balcaen & Ooghe, 2006). Many failure prediction models have therefore been developed and tested on large firms meeting specific criteria concerning asset size, sales level, or the number of employees. Using the same models without country-specific adjustment might result in biased results.

Fixed assets are a crucial component in computing scores for all models. However, due to accounting standards, these values can be misleading as actual values can differentiate from accounting values. According to Norwegian accounting law, all fixed assets must be valued at acquisition cost (Regnskapsloven, 1998, § 5-3). Acquisition cost is defined as purchase price plus potential variable or fixed costs related to the asset (Regnskapsloven, 1998, § 5-4). Real estate companies and real estate developers are significantly impacted by this law as most of their assets are fixed assets. This may result in biased scores for the bankruptcy models.

A substantial share of real estate development projects is structured as separate firms. This is also the case for borrowers in our analysis. For these firms, costs and income will arise at various stages during the project's lifespan. Expenses arise during development, while revenue will only be gathered when the project is sold. Expenses and revenue may therefore arise in different fiscal years. This may paint imprecise pictures of firms' financial health when only looking at one year's accounting statements. This may also result in biased scores for the bankruptcy models.

6.2 Lack of historical performance of crowdlending

Crowdlending has not existed for long. There were only minor crowdlending activities before the financial crisis of 2008. The credibility of crowdlending platforms suffers from this. FundingPartner (2023), Kameo (2023) & Monio (2023) state that the investors would yield a net yearly return of 9%, 8.5%, and 9%, respectively. The platform's skill in managing loans, mitigating default risks, handling the platform's risk, assessing, and monitoring borrowers, managing loan defaults, and handling investor complaints is not documented over time. The lack of historical data is also why there is limited research on crowdfunding and –lending. As mentioned earlier, regulations are still a work in progress. The industry is relatively new, and regulations are yet to be drafted. In addition to a lack of a crowdlending track record, real estate borrowers have profited from the positive development in real estate prices. Since 2018, real estate prices have had a yearly growth of 4.2% (SSB, 2023b). The crowdlending platforms' short span of life and exclusively positive trends in real estate prices may lead to the analysis not reflecting performance in more challenging economic environments. Recent media coverage and development highlight the complexity of the industry and the need for further regulations, despite the challenge of regulating a somewhat unexplored sector. Conclusively, the lack of historical data limits research and drafting of satisfactory regulations for the industry.

6.3 Potential errors while assembling and wrangling data

Due to limited public data sources, we assembled the dataset manually. We have retrieved data as precisely and accurately as possible. Before gathering the data, necessary guidelines and internal rules were set to minimize the margin of error. Despite this, we acknowledge that the risk of error is higher than if the data was gathered automatically or by a certified database. While entering data into our dataset, errors may occur, including typos, transposed digits, incorrect data types, and missing values. Both authors of this thesis were involved in gathering data, which increases the risk of inconsistencies. Gathering data from multiple sources may also lead to inconsistencies. For example, the platforms may state the same exact figures while their argumentation for these differs.

Financial statements were extracted from Proff Forvalt and matched in our dataset on the borrower's legal name. Name changes and other factors forced us to register some financial statements manually. This is public accounting data retrieved from a government agency; thus, it should be highly accurate. Although there are several possibilities of errors in our dataset, we believe that our data management procedures and thorough quality controlling of the dataset and wrangling are satisfactory as preventive measures.

6.4 Population size

Due to crowdlending still being in the early stages in Norway, the number of loans per platform are limited. A small population may result in reduced statistical power, making it hard to find statistical differences or similarities even if they exist (Hoenigm & Heisy, 2001). An example of this can be seen in section 5.2.3, where we tested significant differences among, for example, A- and D-classified loans. There are very few A- and D-classified loans in the dataset, which impacted the significant test reducing its statistical power. Section 5.4.4 is also affected by the small sample size, where figures with larger samples are more interpretable than the opposite.

7.0 Conclusion

The main objective of this thesis was to examine risk differences in credit classification between Norwegian crowdlending platforms. We analyzed credit quality among real estate borrowers across FundingPartner, Kameo and Monio. Due to limited historical and market data, we manually gathered loan data through the platforms' websites. Financial statements and credit scores related to each borrower were extracted and enabled us to apply three well-known bankruptcy models to examine the differences: Altman's Z-score, Ohlson's O-score and Zmijewski's X-score. The bankruptcy model scores were tested to check for significant differences among the platforms and their credit classifications.

The empirical results suggest that Monio are more hesitant than FundingPartner to classify loans with the best credit classifications. However, testing bankruptcy scores suggest that borrowers of A- and B-classified loans at Monio are significantly less risky than borrowers of A- and B-classified loans at FundingPartner. Monio also hosts the riskiest borrowers in the worst credit classification. The default rate for D-classified loans confirms that Monio's borrowers with D-classified loans are riskier than borrowers with D-classified loans at Kameo.

Monio consistently provides their borrowers with superior interest rates for A-classified loans, compared to FundingPartner and Kameo. Hence, lenders who invest in A-classified loans at FundingPartner are not compensated for the additional credit risk compared to investing in A-classified loans at Monio. FundingPartner has the most excessive use of personal and group guarantees. This may explain why most loans are classified as either A or B, despite their borrowers' scores being significantly worse in some bankruptcy models.

Unsophisticated investors presumably cannot identify differences in credit risk across crowdlending platforms, at least not differences across loans with equal credit classification. We believe that our thesis provides a thorough overview of differences in credit assessment that may benefit the decisions of both lenders and policymakers. Lenders are forced to rely on the platforms' incentive to maintain trust, and that it is enough to prevail over the urge to maximize their total loan volume. We sincerely hope that this thesis motivates future researchers to draft propositions of regulations regarding credit assessment, and make solutions to remove the information asymmetry lenders may face.

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