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Facing the crowd

An assessment of credit quality in crowdlending platform portfolios

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Abstract

Crowdlending is a new form of lending, where platforms act as intermediaries between borrowers and lenders. The industry is gaining traction across Europe and the US. However, there has been little research into this field. The purpose of this paper is to analyze the credit quality of crowdlending borrowers. This is done by applying four internationally recognized credit scoring models on a sample of crowdlending- and bank borrowers. We analyze differences between crowdlending- and regular borrowers across these models and the 14 credit ratios they rely upon. We conclude that crowdlending borrowers have lower credit scores than regular borrowers. Furthermore, crowdlending platforms seem quite good at avoiding the lowest quality borrowers. Thus, it can be suggested that they deliberately target a segment of the SME financing market which has been left underbanked, due to credit rationing and –tightening. The study also give insight into several topics worth investigating further, as more data becomes available.

Preface

SMEs access to finance and crowdlending are topics that lie close to our hearts. Especially as one of the authors has founded a SME, and the other author has spent the last year working in a recently founded Norwegian crowdlending platform. Our common interest in entrepreneurialism, disruptive technologies and business models have been supported by learning theoretical frameworks and key principles from inspiring professors during our years at NHH. It is fair to say that this constitutes the foundation for our thesis.

We would like to give a special thanks to Rotem Shneor, associate professor and director of the department for entrepreneurship at the University of Agder, and affiliate researcher at the Cambridge Centre for Alternative Finance. His insights on the current research and academic development in the field of alternative finance have been vital to us. We would also like to thank, co-founder and CEO of FundingPartner, Geir Atle Bore. He has introduced us to international crowdlending platforms and shared his perspectives on the industry.

Last, but not least, we would like to thank our supervisor, Associate Professor at NHH, Aksel Mjøs. His guidance and facilitation has been vital throughout this period. His advice on the topic and research design has helped us overcome a seemingly daunting task.

Sincerely,

Jørund Thomassen Gjesvik and Olav Hestmann
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Contents

1. Introduction

In this thesis we will study the credit quality of companies receiving loans via crowdlending platforms. We will apply internationally recognized credit risk assessment theory on a sample of companies borrowing through French crowdlending platforms. With this we will investigate what type of risks crowdlending investors are facing, and also whether crowdlending platforms manage to mitigate these.

Crowdlending, sometimes referred to as P2P lending, allows individuals or companies to raise debt through multiple lenders (investors). Crowdlending is the largest and fastest growing type of crowdfunding in Europe, with lending volumes growing from €706m to €5bn between 2013 and 2016 (Ziegler, et al., 2018). Most platforms screen loan applications, evaluate credit and carry out careful due-diligence before making projects available for their investors (Li, 2016).

Crowdlending platforms target the SME segment, which make up 99% of all enterprises and two thirds of all employees in the EU countries (Eurostat, 2015). In the aftermath of the financial crisis and Basel III capital accords, a significant credit tightening amongst European banks has affected SMEs across all European countries severely (Altman, Esentato, & Sabato, 2016). A similar sign of credit tightening amongst SMEs in Norway was observed by Hetland, Mjøs and Zhang (2018). Thus, a surge in crowdlending might provide much needed relief to the SME financing market.

At the same time, fixed income investors have for many years faced record low yields in the corporate bond markets (Federal Reserve Bank of St. Louis, 2018). With low, or even negative interest rates, investors seeking positive inflation-adjusted returns have few options except for high yield bonds or equity markets.

Crowdlending platforms have no legal obligation to carry out due-diligence, and there is limited insight and transparency into the credit asessment on borrowers. This highlights the vulnerability of the investor's decision process (Ahern, 2018). Trust is therefore important for investors assuming that credit quality and associated risk is priced correctly (Zhang, et al., 2017).

In a recent call for papers, Shneor and Maehle (2016) point out that reasearch into all types of crowdfunding remains limited. We hope to contribute to the understanding of crowdlending and its place in the financial markets, by investigating the risk profile of the companies obtaining this type of funding. Hopefully, this will also shed light on the challenges of adverse selection, information assymetry, and how crowdlending platforms and their investors could be affected.

We find that crowdlending borrowers have a poorer credit quality than that of companies borrowing from regular banks. Furthermore, we find that crowdlending platforms are just as good as banks at rejecting the companies with high likelihood of default, suggesting that crowdlending platforms are deliberately targeting an underserved segment of the SME borrowing market. Thus, it can be argued that the crowdlending platforms address a riskier segment than banks, without exposing their investors to companies that are likely to default. This could indicate that the platforms are aware of the information asymmetry problems investors face, and try to adjust for them.

We also find that crowdlending platforms lend to both high and low quality borrowers. Most of which are mature and already have received financing through other financial institutions. This could indicate that companies use crowdlending platforms to either increase their total credit facilities, or improve terms on current debt. Crowdlending platforms could therefore both supplement and compete with banks.

In the next section we will provide a thorough explanation of how crowdlending platforms operate, and how they fit in the financial market. We will also discuss the most relevant theories for analysing our results. In section three, we will introduce the credit scoring models and the rest of our methodical approach to investigate our research question. Section four provide insights into our dataset and how it was obtained. The model results will then be presented in section five, before they are discussed using relevant theory in section six.

2. Background and litterature

In this section, we will provide a brief introduction to the background for our thesis, and relevant theory that will be used for discussion in section six.

2.1 About Crowdlending

Crowdlending can be defined as debt-based transactions between individual investors, and a borrower. One or several investors contribute to a single loan and receives down payments and interest stipulated by the loan contract. The crowdlending platform facilitates the matching of investors and borrowers through an online marketplace. It is thus an intermediary, attracting both investors and borrowers. Platforms take care of transferring funds, organizing legal framework, and in many cases, they dictate the terms of the loan. Furthermore, many pursue the borrower on behalf of investors in the event of default. Some platforms even have their own debt collection branches (Funding Circle, 2018). This is very much in line with the *raison d´être* for banks argued by Diamond (1984), namely that banks monitor borrowers and enforce the repayment of funds to depositors.

Crowdlending can be split into two main categories: Business lending and consumer lending. (Baeck, Collins, & Zhang, 2014). The first crowdlending platforms began in 2005 and 2006, with UK based Zopa and US based Prosper. The early platforms focused solely on consumer lending serving private individuals' financial need. The first UK based business crowdlending platforms were founded in 2010 (Moenninghoff & Wieandt, 2012). Since then, business crowdlending has experienced a rapid growth in the UK. Business crowdlending now outranks all other forms of crowdfunding in the UK market, with a volume of £1,2bn in 2016. This constitutes 15% of all bank lending to small businesses. If we add real estate business lending, which in the UK is categorized separately, the volume surpasses £2bn.

In the rest of Europe, business crowdlending is experiencing triple digit growth rates, with a total volume of €212m in 2015. The crowdfunding industry is still in an immature state with new players entering frequently adding to the total of 267 European platforms (Ziegler, et al., 2018). In our thesis, we will focus on business lending.

Platforms typically offer loans with maturity between 6 and 60 months (Credit.fr, 2018), varying from short to long term debt. Average loan size for crowdlending platforms was €111 633 in 2016 within Europe (Ziegler, et al., 2018). Interest rates can be as low as 1,9%, but typically range between 6-10% (Funding Circle, 2018). In addition, platforms offer both secured and unsecured loans to their borrowers (Lendix, 2018).

Platforms do not invest their own equity in loans. Thus, a default would not imply direct losses. Still, they must maintain a good reputation amongst investors in order to attract capital. Without this, the platforms would go out of business. Therefore, most platforms report their investors' overall performance. This includes failed repayments, defaults and aggregated losses due to defaults. Most platforms have made several measures to control the quality of their borrowers, including credit models, credit ratings and careful review of applications to support the lending decision (Hernandez, et al., 2015). A 2017 survey shows that the single factor European platforms fear the most, is "bad actors" ruining the business' reputation amongst investors (Ziegler, et al., 2018)

Ahern (2018) argues that most crowdlending platforms share little or no financial data with investors, which is necessary to make an independent and informed decision. Often information such as platforms' credit assesment process is not transparent, which could make it difficult for investors to understand how the platform price risk. He also points to herding behavior and irrational intuition of unprofessional investors as potential issues.

2.2 Crowdlending platforms' role in the capital market

Crowdlending is a relatively new concept, and there still is a need for literature exploring its role in modern capital markets. As crowdlending matures, we are seeing some early signs of capital market integration.

2.2.1 Crowdlending platforms compared to banks

One important difference between crowdlending and modern banks, is the capital reserve requirements. Banks allow depositors to withdraw money quite freely, and also assume most of the risk associated with lending. If a loan defaults, the cost is carried by the banks' equity first, leaving depositors with greater robustness and security (Fama, 1985). Furthermore, if the bank defaults, a deposit guarantee scheme will ensure that all depositors get a certain amount, which in the EU is €100.000 (Council of the EU, 2017). Through this scheme, and the Basel III accords, banks are required to maintain a certain ratio of equity to debt (Bank of International Settlements, 2017). In contrast, crowdlending platforms offer no security to their investors. Thus, they have limited capital requirements, which reduce their costs compared to banks (Pasiouras, Tanna, & Zopoundis, 2009). On the other hand, as crowdlending platforms merely pass the risk on to the individual investors. A higher interest rate could therefore be interpreted as a compensation for the increased risk facing investors.

Another important factor to highlight is the sources of revenue, and thereby the incentive structure for crowdlending platforms. Banks rely on spread from loans, as well as fee-for-service products such as insurance and mutual funds. They also have separate income streams on credit cards and leasing. This generates profitable synergies and lock-in effects (DeYoung & Roland, 2001). Crowdlending platforms are highly focused on facilitating loans for businesses and are not differentiated across multiple products. However there are no evident barriers stopping platforms from expanding their product portfolio. The high degree of spesialization could be due to efficiencies of scale.

Most crowdlending platforms generate revenue in the same way as corporate brokerages, by taking transactional fees on successfully brokered loans (Garret, 2017). This means that crowdlending platforms have no incentives affecting their interest rate decisions, as they would not benefit from the interest spread.

2.2.2 Crowdlending platforms compared to bond markets

One could also argue that crowdlending platforms share similarities with bond markets. A bond market is a financial market where corporate debt securities are issued and traded. In the same way as bonds, crowdlending allow companies to raise credit from private investors which in return receive interest. As with regular bond markets, some platforms offer secondary markets, where investors can buy and sell positions in individual loans before they mature, thus ensuring better liquidity for investors (Funding Circle, 2018).

In bond markets, rating agencies such as S&P and Moody's provide independent credit ratings for each bond or company. The aim is to reduce information assymmetries between borrowers and investors. In a study by Steiner and Henke (2001), it is shown that credit rating downgrades made by S&P and Moody's have a significant impact on German corporate bond prices. This means that bond investors tend to rely on credit ratings by independent rating agencies. This is because independent ratings are meant to mitigate agency problems, as the rating agency itself has no interest in setting a good or bad rating (Steiner & Heinke, 2001). Amongst the largest European crowdlending platforms, Lendix (2018), Credit.fr (2018), and FundingCircle (2018), credit ratings are mostly done internally, without external validation. This is an important difference between crowdlending- and regular bond markets.

While bonds are normally in the hundreds of millions or billions of euros, crowdlending loans are in the hundreds of thousands or low millions (Ziegler, et al., 2018). This is why SMEs do not operate within bond markets, but rather take use of crowdlending platforms which have lower fees and operating models adjusted to loans of this size. Bonds and crowdlending loans are similar at nature, but serves two different business size segments.

2.2.3 Institutionalization and integration in professional capital markets

In 2016, 36% of all business crowdlending investments were done through “auto-investing”, where the investor choose how much to invest, selecting a risk preference instead of individual loans (Ziegler, et al., 2018). This reduces the investor’s cost of managing a portfolio (Funding Circle, 2018). On the other hand it lowers transparency and may result in unfavourable lending decisions.

Recently, crowdlending platforms have begun raising capital from institutional investors and securitizing parts of their portfolio. In 2016, institutional investors accounted for 28% of all funding through UK crowdlending platforms (Zhang, et al., 2017). The same year, Funding Circle issued their first Asset-Backed Security which was split into six tranches of loans, totaling £130m. The security was externally rated by Moody’s (Curti & Klotz, 2016). According to Funding Circle (2016) this was the first security of its type in Europe. Another example is the Swedish platform Lendify, which issued a SEK 200 million bond in 2017 to fund its growing portfolio of individual consumer loans (Nordic9, 2017).

In the more developed US market, a new category of crowdlending, called “Balance Sheet Business Lending”, has been introduced. In this category, crowdlending platforms raise capital from retail and professional investors to their own balance sheets, and use it to grant loans. This scheme is normally run in tandem with the traditional crowdfunding process where individual investors pick their own investments. While business crowdlending grew from $1bn in 2014 to $1.5bn in 2016, balance sheet business lending grew from $1.1bn to $6.1bn. (Ziegler, et al., 2017).

The increasing popularity of auto-invest and fund options, and the influx of institutional investors could lead to economies of scale. Larger platforms could more easily fund loans using funds on their balance sheet, thus increasing the speed and successful funding rate of the platform. A possible effect from economies of scale could be entry barriers for new platforms. Findings from the US market show a 50% decline in new platforms between 2015 and 2016, with balance sheet business lending coincidentally growing by 160% in the same period (Ziegler, et al., 2017).

The profesionalization could also increase requirements for due diligence and portfolio risk management. Portfolio risk management through stipulating quantitative ceilings for aggregate exposure would reduce individual risks related to specific customers, sectors or industries (Raghavan, 2003). This could further strenghten the economies of scale, and also lead to entry barriers as platforms must build risk assessment capabilities.

2.3 Credit market theory

In this section, we will summarize the most relevant credit market theory that can be applied to our thesis.

Stiglitz and Weiss (1981) proved that credit rationing can exist in an equilibrium market, as there exists an optimal interest rate which maximizes expected return to the bank. They define credit rationing as circumstances where it is impossible to distinguish applicants that are granted or rejected loans. Even though the rejected companies would accept a higher rate. Banks do not see it profitable to raise interest rate or change collateral requirements, as this could incentivize riskier behavior from the borrowers, or lead to adverse selection effects.

Stiglitz and Weiss (1981) further argue that interest rate serves as a monitor device due to it’s implicit relationship with the selection of borrowers and their incentives. If interest rates increase it could potentially make safe projects unprofitable and force borrowers to choose riskier alternatives, incentivizing a structure of high risk with little potential reward for banks. Similarly, a high interest rate could potentially attract riskier profiles resulting in higher risk of default and thus lower overall profitability for banks.

Altman, Esentato and Sabato (2016) claim that the Basel III capital accords have led to a heavy credit tightening amongst European banks, affecting SMEs across all European countries severely as they have no available bond market. They also point out how the high yield bond market for large European corporations have increased from €100 billion in 2010 to €500 billion in 2015, due to the credit tightening. A similar sign of credit tightening amongst SMEs in Norway was found by Hetland, Mjøs and Zhang (2018).

Information asymmetries are one of the cornerstones of banks' existence (Leland & Pyle, 1977). Unlike private investors, banks have better means of identifying probability of repayment with historical information and relationship based data (Schenone, 2010). Agarwal and Hauswald (2010) shows that banks' accuracy of private information is a function of distance. This can be seen in light of the argument made by Degryse and Ongena (2005), that geography is related to asymmetric information not transport cost. Information asymmetries make it common to define banks as "outsider" nor "insider", depending on their relationship with the borrower. Banks that use the relationship to reduce information asymmetries, engage in relationship banking.

Scheone (2010) studied the effect of information asymmetries, by measuring the importance of publicly available information to the ability to switch lender, finding that interest rates fall post IPO and relationship intensity decreases. When banks face the same information about companies, the banking relationships' value falls, leading to weakened lock-in effect and lower switching costs. Kim, Kliger and Vale (2003) finds that switching cost is about 4%, whereas lock in effect accounted for 25% of the switching costs.

Banks reduce asymmetric information by monitoring borrowers and enforcing payments (Altman, Esentato, & Sabato, 2016). If crowdlending platforms are unable or unwilling to act as formal intermediaries', individual investors are directly exposed to adverse selection risks and moral hazard problems (Ahlers, Cumming, Günther , & Schweizer , 2015). The "crowd" may underperform due to lack of expertise, limited resources and limited incentive, unwilling to bear the cost of governance. Therefore, finding platforms that act as good intermediaries is important to make successful crowdlending investments (Freedman, 2011). When crowdlending platforms allow investors to pick specific loans, Mohammadi and Shafi (2017) finds a performance gap between institutional- and private investors. Institutional investors' ability to process, analyze and evaluate loans, leads to better performance. This could also suggest that the platforms' interest rates are not perfectly pricing the underlying risk.

Still, faith in platforms' due dilligence remains high, with 59% of investors in UK platforms relying on platform due dilligence when investing. (Zhang, et al., 2017).

Hetland and Mjøs (2012) looks at who borrows in cyclical stages and finds that in times of bust, bank-switching companies are more profitable and less likely to exhibit loss or go bankrupt. Presumably because outsider banks are more careful, or the information asymmetry is less prevalent in stages of contraction. In times of expansion companies switching lenders exhibit a worse financial performance than those extending loans from their current bank.

Banks perform a certification role, signalling that a company receiving a loan is of high quality. James (1987) proved this by looking at signalling of new loans in comparison with abnormal stock returns.

3. Methodology

To assess the creditworthiness of companies borrowing through crowdlending platforms, we will apply a set of credit models that assign credit scores to each company. These credit scores will be compared with credit scores from French companies, that have borrowed through other financial institutions than crowdlending platforms. Three of the four models also provide cut-off scores that indicate high likelihood of default.

3.1 Selecting credit models

Credit assessment models can be split into two categories: Credit rating models and credit scoring models. Credit rating models are quite detailed and take a long-term view. They are mainly associated with corporate clients, large institutions and the public sector. Usually they are used by independent rating agencies (Allen, 2002). Scoring models are traditionally focused on short term, and are also known as default prediction models. The scoring models are in general much simpler than credit rating models, requiring less financial data about the company and the economy in general. Combined with a relatively high accuracy, this makes them ideal for assessing loans to private individuals or SMEs (Sabato, 2010). Credit scoring models is common practice amongst banks, with 70% of all US banks using them in their small business lending (Mester, 1997). Our data sample is cross sectional, due to the limitations of the Amadeus database, which is further discussed in section 4.2. Combined with a limited set of obtainable variables, this excludes credit rating models from being a viable option for us. Thus, we will proceed using credit scoring models.

The first modern credit scoring models were developed in the 1960s. Since then, multiple models have been introduced. Four methodologies have been popular: univariate analysis, risk index models, multivariate discriminant analysis (MDA) and conditional probability (logistic) models. While there are some studies with univariate and risk index models, MDA and logistic models have been dominant (Balcaen & Ooghe, 2006).

MDA was introduced by Altman (1968) in his Z-score model which still is one of the most widely used in the world. Although popular, the MDA method has some shortcomings as pointed out by Ohlson (1980). These shortcomings are discussed further in section 7.2.3 on credit model limitations.

Despite the disadvantages discussed in section 7.2.3, credit scoring models are still an efficient and relatively accurate method for estimating default risk (Altman & Sabato, 2013). In our selection of models we prioritize models that are frequently referenced in internationally. We also look for models that do well across multiple countries and sectors. Another important factor is the availability of model inputs, which must be downloaded from Amadeus.

All models define “default” as bankruptcy declared by court (Balcaen & Ooghe, 2006). In section 7.2.3 we discuss potential issues with this definition, and why it reamins the common default definition when estimating these models. We will elaborate on the individual models and reasons for selecting them in the upcoming sections.

The models mostly use different credit ratios. For the few ratios that overlap, the definition of the credit ratio components is the same between the models. A table showing all credit ratios used in each model can be found in appendix 9.4. Table 3.0 summarizes the main features of the models. A comprehensive list of credit scoring models can be found in a paper by Balcaen and Ooghe (2007).

Table 3.0: Credit models applied to our analysis.

Model	**Altman Z''-score** (1983)	**Altman-Sabato** (2013)	**Gloubos-Grammatikos** (1984)	**Keasey-McGuinnes** (1990)
Estimation	Discriminant analysis	Logistic regression	Discriminant analysis and logistic regression	Logistic regression
Sample	33 manufacturing firms with avg asset size $6m	2000 SMEs, no specific sector with sales less than $65m	29 industrial firms.	43 firms with data available on Datastream
Sample years	1946-1965	1994-2002	1977-1985	1975-1984
Sample country	USA	USA	Greece	UK
Cut-off score	Safe zone > 2.6 Grey zone: 2.6-1.1 Distress zone < 1.1	N/A	0.944	0.7939

3.1.1 Altman's Z''-score model

The Z-score model was developed by Altman (1968) and is one of the first modern credit scoring models created. It was re-estimated in 1983, and to this date, it is probably the most widely used credit scoring model. The model is developed using the MDA method, which means that you split all sample firms into two categories: bankrupt or non-bankrupt. A score is then provided, which tells us which of the two categories the company is most similar with (Altman, Iwanicz-Drozdowska, Laitinen, & Suvas, 2014).

There are three different versions of the Z-score model: The original Z-score model from 1968 (Altman E. I., 1968) and two versions of the re-estimated model from 1983 (Altman E. , 1983). The 1983 models are based on the same sample as in 1968, but are specifically designed for different types of companies than the original model. The Z'-score model which is made for private industrial and manufacturing companies, and the Z''-score model is designed for private non-manufacturing companies (Altman, Iwanicz-Drozdowska, Laitinen, & Suvas, 2014). In our study, we are dealing with a variety of companies across many sectors, the Z''-score model is the best fit for our purposes. This model is featured in most international comparative studies. The model is as follows:

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

$$X_1 = \frac{Working\ capital}{Total\ assets}$$

$$X_2 = \frac{Retained\ earnings}{Total\ assets}$$

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

$$X_4 = \frac{Book\ value\ of\ equity}{Book\ value\ of\ total\ liabilities}$$

In a study by Altman, Iwanicz-Drozdowska, Laitinen, & Suvas (2014), the Z''-score model is tested on samples of companies from more than 30 individual countries. This includes a sample of approximately 6000 failed and 16 000 non-failed French companies. The study provides a scale that runs between 0.5 and 1, where 0.5 means that the model is completely random and 1 means that the model is perfectly accurate. The Z''-score model scores 0.74 on the French sample, compared to an average score across all sampled countries of 0.75. In other words, the model proves to work equally well in France compared to other countries. This indicates that the model is suitable for our purpose, although it does not have a perfect accuracy.

3.1.2 Altman-Sabato model

The Altman-Sabato (2013) model has quickly become a recognized credit scoring model, in part due to its co-author Edward Altman who also created the Z''-score models. The Altman-Sabato model is developed using logistic regression on a panel of 2 000 US SMEs with sales less than $65m, over the period 1994-2002. In the same study, the model is benchmarked against the Z''-score model. This is done by running them on a holdout sample of 26 US SMEs that went bankrupt in the period 2003-2004. While the Z''-score model achieved an accuracy of 69%, the Altman-Sabato model achieved 87%. In other words the study suggest that the

Altman-Sabato model has a 26% higher accuracy in predicting bankruptcy amongst SMEs. The model is as follows:

$$KPG = +53.48 + 4{,}09\ln(1 - X_1) - 1.13\ln(X_2) + 4.32\,(-\ln(1 - X_3) + 1.84\ln(X_4) + 1.97\ln(X_5)$$

$$X_1 = \frac{EBITDA}{Total\ Assets}$$

$$X_2 = \frac{Short\ Term\ Debt}{Equity\ Book\ value}$$

$$X_3 = \frac{Retained\ Earnings}{Total\ Assets}$$

$$X_4 = \frac{Cash}{Total\ Assets}$$

$$X_5 = \frac{EBITDA}{Interest\ expenses}$$

Due to its improved accuracy over the original Z''-score model, we include the Altman-Sabato model in our study. The model has yet to be internationally tested, we therefore choose to keep the Z''-score model.

3.1.3 Gloubos-Grammatikos model

The Gloubos-Grammatikos model was developed by Gloubos and Grammatikos (1984) on a sample of Greek companies. They used both the logit- and the MDA methodology, and thus two versions of the model exist. The model is frequently referred to in failure prediction literature. In a study done by Ooghe and Balcaen (2007), the model outperforms seven other wellknown credit scoring models, including the original Altman's Z-score from 1968. This is done by running all models on the same sample of companies, and finding which models achieves the highest accuracy in predicting bankruptcy. The study is performed on a sample of Belgian companies, which adds relevance for our sample, due to Belgium's geographical and cultural similarities with France. The logit version of the model only contains three variables, while the MDA-version contains five. We choose the MDA-model as it outperforms the logit version of the model in the Ooghe and Balcaen study. The model is as follows:

$$GG\text{–}Score = 4.423 - 2.044X_1 + 4.421\,X_2 - 4.404\,X_3 - 2.778X_4 + 4.423X_5$$

$$X_1 = \frac{Current\ assets}{Current\ liabilities}$$

$$X_2 = \frac{Working\ Capital}{Total\ assets}$$

$$X_3 = \frac{Long\ term\ liabilities}{Total\ assets}$$

$$X_4 = \frac{\frac{P}{L}\,before\ taxes}{Total\ assts}$$

$$X_5 = \frac{EBITDA}{Short\ term\ liabilities}$$

3.1.4 Keasey-McGuinnes model

The Keasey-McGuinnes model was developed by Keasey and McGuinnes (1990) on a sample of British companies. It is estimated using a logit model. Similar to the other models chosen for our analysis, it is widely referenced, and has a proven track record. In the previously mentioned Ooghe and Balcaen (2007) study, the Keasey-McGuinnes model comes out on a strong 2^{nd} place after the Gloubos-Grammatikos model. The model only contains three ratios, and is therefore quite simple compared to the others. The model is as follows:

$$KM\text{–}Score = -0.0881 - 0.0316X_1 + 0.2710\,X_2 + 0.3227X_3$$

$$X_1 = \frac{Equity}{Liabilities}$$

$$X_2 = \frac{Purchases}{Accounts\ payable}$$

$$X_3 = \frac{\frac{P}{L}\,before\ taxes}{Sales}$$

3.2 Credit ratios

In addition to running pre-defined credit models, a simple analysis all of credit ratios featured in our models can also say something about a company's financial health. The models rely on ratios that cover profitability, liquidity, leverage and interest coverage. In total there are 13 different ratios used across all models. A complete list of ratios and in which models they appear in, is shown in appendix 9.4.

All models use a profitability measure. Three out of the four models use some form of earnings / total assets ratio. The models developed by Altman also use retained earnings/total assets. Altman (2014) argues this ratio is a good way of understanding the long term profitability of the firm without accessing historic data.

Liquidity is also present in all models, and is an important indicator of how well the company manage cash. Working capital/total assets is the most frequently used ratio.

All models have some form of leverage measure. This could be particularly useful to analyze, as it would tell us whether the companies borrowing through crowdlending platforms are already highly levered. They might use crowdlending platforms to "lever up". The equity / total liabilities ratio seems to be the most frequently used leverage-ratio in the models.

Interest coverage is important for measuring the company's ability to pay its interest without depleting its equity. A typical ratio is EBITDA/Interest expenses. Interest coverage ratios are only a part of the Altman Sabato (2013) and Gloubos Grammatikos models (1984).

3.3 Loss given default

Credit risk is based on the components probability of default and loss given default (LGD) (Lindgren, 2017). Loss given default is what the lender expects to lose on default, thus the key elements to estimate LGD are the covenants regulating the borrower, and the collateralization set out in the loan contract (Asarnow & Edwards, 1995). Crowdlending is a relatively new market in France, and it is difficult to obtain LGD on loans. Neither Lendix (2018) nor Credit.fr (2018) present statistics over their LGD or recovery rates. A proxy could be

FundingCircle in the UK market, which has recovery rates of 48%, implying a LGD of 52%. In contrast the LGD rate for French SME borrowers is about 20% (European Banking Authority, 2013).

A study by Li (2016) finds that Swedish crowdlending loans on average tend to have lower collateral than traditional bank loans. Swedish and French platforms operate with similar terms, namely not requiring personal guarantees or collateral from borrowers. It is thus reasonable to assume that the loans on French platforms have less collateral than regular bank loans. Lower collateral would imply a higher LGD. We can therefore assume a higher LGD amongst French crowdlending borrowers, which increases the riskiness of the loans.

3.4 Coarsened Exact Matching

To test our hypothesis, we need to make sure we are comparing SMEs with similar characteristics, thus reducing the risk of endogenous results. The credit scoring variables analyzed in our method may vary depending on factors such as industry and region. We therefore deploy the matching procedure *Coarsened Exact Matching* ("CEM"). The purpose of this procedure is to match companies borrowing through crowdlending platforms with companies of similar characteristics in the general population of French companies having received loans. Thus, we are trying to satisfy the "ceteris paribus" condition of causality by approximating randomnization. Still, one must bear in mind that all matching analyses merely approximate randomnization, and does not necissarily achieve this fully (Iacus, King, & Porro, 2012). A brief overview of the theory and idea behind CEM is provided in the section below. For a detailed description, see Iacus, King & Porro (2012) and King et. al. (2007).

CEM is part of the Monotonic Imbalance Bounding class of matching methods. It relies on a stratification approach that can be summarized in three steps (Iacus, King, & Porro, 2011):

1. Each variable is coarsened according to a pre-defined criterion, meaning that each variable is split up in sepearate "bins" of pre-defined values. For instance the company size variable is split into small, medium, large and very large.

2. Exact matching is applied so that all observations are sorted into strata. Each stratum represent an unique combination of the coarsened variables included in the matching procedure.
3. Strata containing treated and control units are retained, while "incomplete" strata are discarded. Given more than one match per treated unit, CEM assigns weights to the control unit to adjust for different stratum sizes.

We chose CEM over other methods such as propensity score matching and other equal percent bias reducing methods as it performs better for reducing imbalance, estimation error and bias (Iacus, King, & Porro, 2012). This is because we can define the coarsening before the algorithm is applied, by manually deciding each bin size. This allows the flexibility to combine exact and broad matching. We can do exact matching on variables that should be exactly matched, such as company legal type where we i.e. only want to match limited liabilities companies with other limited liabilities companies. At the same time we can match on broader crierions, as we for instance do with company size, where we are matching based on broad definitions of company size.

In the CEM procedure, the tradeoff lies in selecting the bin sizes, and thus the degree of coarsening applied to each variable. Narrower cut-off points imply smaller bins of data, and thus less diverse observations within each stratum. This leads to lower imbalance in the data (King, Blackwell, Iacus, & Porro, 2007). On the other hand, as we are not defining a matched sample size ex ante, we risk having limited matches and thus a less efficient model (Iacus, King, & Porro, 2012). Variables and bin sizes are described in section 3.4.1.

Beyond the general ignorability assumptions, CEM does not rely on any assumptions for the data generation process (Iacus, King, & Porro, 2012).

3.4.1 Variables and bin sizes

To analyze differences in credit worthiness, we need to compare samples of companies that share the same characteristics. This means matching companies on the covariates we believe are likely to be endogenous, and are possible to obtain. Furthermore, we must be careful not to use financial covariates, as these are likely to cause multicollinearity issues in our regression models. The only financial covariate we match is the size of total assets, which is matched using broad "bins" to avoid multicollinearity.

The CEM procedure does not allow for selecting sample size ex ante. This means that we must be careful deciding on bin sizes. If the bins are too wide, the procedure will not reduce imbalance. If the bins are to narrow, the model could become less efficient, as we are less likely to find matches.

A short description of each variable and cut-off point follows below:

Total assets: Total assets is used in many of the ratios we are analyzing in the credit scoring models, and is therefore challenging as a matching variable. At the same time, total assets is a widely used measure of company size. Company size could clearly cause endogeneity in the model, as the financial properties of large and small companies may vary a lot. Size could also affect access to credit (Hetland, Mjøs, & Zhang, 2018). In addition, crowdlending platforms primarily cater to the SME-market, and thus we want our sample to be matched with other companies of similar size. To compensate for the fact that total assets is one of the variables in the credit scoring model, we choose relatively large cut-off points, following the company size categories used by Bureau van Dijk (2018).

Company size	**Total assets**
Small	< €2 million
Medium	€2 to 20 million
Large	€20 to 200 million
Very large	> €200 million

Accounting year: This is to ensure that we have the same accounting years, i.e. a company that received a loan in 2015 and thus has accounting data from 2014 is matched with other companies with accounting data from 2014. By doing this, we ensure that our data set is not contaminated with time specific economic effects that could affect individual companies or sectors.

Region: This is to control for potential regional differences between borrowers, their access to finance and capital structures. Some regions may be influenced by local legislation, culture, distance to adressable markets and capital providers. This could have endogenous effects on our model, as a company situated in Provence could have significantly different conditions for accessing capital than a company based in Paris. We have split the regions into the 18 administrative regions of France.

NACE code: The capital structure and sources of financing may vary greatly between industries, i.e real estate companies have quite different balance sheets than tech-companies. As there are more than 1000 different NACE codes, we have coarsened this variable so that it matches companies where the first two NACE code numbers match. This means we can compare companies within the same industry, and is in accordance with similar analyses carried out by Statistics Norway (Cappelen, et al., 2016).

Company legal form: France has six different legal forms for companies, ranging from sole proprietorship to limited liability companies. As the judicial properties of company forms are different, it is reasonable to assume that access to credit will vary as well. For a limited liabilities company, debt might be a more tempting option than for a sole proprietorship where you are personally responsible for company debt. We therefore require exact matching on this criterion.

Age: Company age could also affect access to financing. Older companies should be more likely to have financing from banks, due to the effects of relationship banking discussed in section 2.3. We coarsen this variable into nine categories, following the classification done by The Norwegian Central Bank (Norges Bank) in their SEBRA-model (Berhardsen & Larsen, 2017). Companies are sorted by each year until eight years. All companies older than eight years are put in the same category. We require an exact match across the nine categories.

To summarize, we are matching companies that are of somewhat same size, originate from the same region, have the same legal charecteristics, operate within the same industry, and have the same life cycle.

The goal of matching is to produce a dataset which allows for both efficient and unbiased regression results.

3.4.2 Measuring and reducing imbalance

A reduction in potential bias can be measured through the *L1* imbalance statistic which is given by:

$$L_1(f,g) = \frac{1}{2}\sum_{l_1 \dots l_k} |f_{l_1 .. l_k} - g_{l_1 .. l_k}|$$

where *f* indicates treated and *g* indicates control group.

A L_1 statistic of 1 signals perfect imbalance, while a statistic of 0 signals perfect balance. According to King et.al. (2007) the *L1* statistic is not important in itself, but should be used as a benchmark. The goal of the matching procedure is thus to reduce the *L1* statistic so that:

$$L_{1_{pre-treatment}} > L_{1_{post-treatment}}$$

3.4 Statistical models

Due to the matching process, we hope to have reduced the probability of endogeneity in our results. As we have chosen small bin sizes there is little need to further control for these variables in the statistical models. The only variable with large bin sizes is the total assets size, which we intentionally do not want to control too much for, as this might cause multicollinearity issues. Our statistical models therefore follow a single regression pattern:

$$Dependent\ variable\ (model, ratio\ etc.) = \propto\ + \beta_1 crowdlend +\ \mu$$

OLS is used as estimation technique, and heteroscedasticity is adjusted for with robust standard errors where necessary.

4. Data

Getting good data samples for crowdlending is a challenging exercise, and probably an important reason why there has been little research on the subject so far. The markets for business crowdlending are immature and fragmented, so finding sources with substantial sample size is difficult. Countries have varying and limited standards of general financial reporting on companies. In addition, we have yet to encounter a European crowdlending platform that is willing to share an uncensored loan book, or give out financial data on its borrowers. Crowdlending platforms are focused on establishing credibility and gain trust from investors, as they do not use external auditors to verify the quality of their loan evaluation. Many do this by reporting key figures or censored loan books. Unfortunately, this data is not sufficiently detailed for our analysis.

In our credit score analysis of SMEs receiving loans through crowdlending platforms, we rely on data gathered from French crowdlending platforms, matched with financial data from Amadeus.

4.1 French crowdlending platforms

The French crowdlending market is the third largest in Europe, after UK and the Netherlands with a total loan volume of €71m in 2016 (Ziegler, et al., 2018). The French market is by far the most transparent of the three markets, as Dutch company registers provide limited financial data, and UK platforms generally refuse to give access to uncensored loan books and project records.

Although French platforms do not give out structured loan books with French company ID numbers (SSIN), some of them keep an online registry of all loans that have been financed through their platform. By carefully analyzing all French platforms we managed to track down the ones with enough available data. Through programming and deploying web scrapers, we have amassed a dataset containing all loans given out by the two largest French platforms, Lendix (2018) and Credit.fr (2018), that are available online. The dataset contains 645 companies, with essential information such as date of origination, volume, credit score, interest rate, company name, industry, region, address with more. Lendix and Credit.fr only provide loans through crowdlending, and do not engage in any other crowdfunding activities. Thus, we do not know whether the sample companies have used other forms of crowdfunding in the past.

Based on this information we have been able to manually match 475 of the companies with their respective SSIN through the French company registry infogreffe.fr (2018). To minimize the risk of error sources, we have only considered a company as a match when the search has yielded one alternative and where industry, name, address and region have proved a 100% match with that of our target.

4.2 Amadeus database

BvD Amadeus is a search engine and database which contains comprehensive financial data on 21 million companies across Europe (Bureau van Dijk, 2018). As companies report financial data to the French public company register, this data can also be found through Amadeus. Amadeus has financial records for 332 of the original 475 companies, in the years between 2014-2016. It is clear that the Amadeus database does not contain information about all French companies.

Furthermore, we have downloaded a large dataset of all French companies in the Amadeus record. These will be matched with crowdlending borrowers to produce a control group.

4.2.1 Variables

To get the variables needed to conduct our analysis, we looked at our credit models to decide what financial data was needed. Understanding the reporting standards of French companies enabled us to compare variables described in our credit models with data retrieved.

To give an example; In the credit score model Altman-Sabato and the Z''-score models, retained earnings is an important variable applied to measure profitability. Unfortunately, Amadeus does not provide retained earnings as a variable directly. By checking French accounting law, we found that in France, other shareholders equity is divided into reserves and retained earnings (“reserve comptable”, “report á nouveau”). Reserves is defined as retained earnings allocated to law-regulated reserve funds, and therefore it is just another measure of retained earnings (Legifrance, 2007). After cross checking with BvD Amadeus’ French office, we validated that Amadeus were in fact reporting other shareholders capital in accordance with French accounting law, and thus represent retained earnings. A table showing all variables can be found in appendix 9.5.

4.3 Preparing data for analysis

In this section, we will describe how we prepare our data for analysis, through cleaning it for outliers and missing values, and matching the treatment and control group through CEM.

4.3.1 Pruning the data set

To get valid results, we have to further clean the data obtained from Amadeus. Missing records and values occur frequently in the database, due to lack of reporting or technical issues. These can lead to errors in our models, and we must therefore remove them. Furthermore, we clean duplicate values and outliers, to make sure that remaining data is complete and of sufficient quality to conduct our analysis.

4.3.2 Matching control- and treatment group through CEM

As discussed in section 3.4, we apply CEM in order to match our treatment group of crowdlending borrowers with a control group consisting of regular French companies that have borrowed through financial institutions.

As discussed in section 3.4.2, a successful CEM procedure is defined by its imbalance (“L_1”) reduction. In our procedure, $L_{1_{pre-treatment}} = 0.9652$ while $L_{1_{post-treatment}} = 0.7803$. Thus, we can conclude that the matching procedure has fulfilled its purpose in reducing imbalance.

The CEM procedure yields 23 893 unique strata, of which 100 are matched, meaning they contain both treated and control observations. Our treatment group is reduced from 125 to 105.

The reduction comes from companies in our treatment group that have not found a control group company with similar characteristics, based on the variables and bin sizes defined in section 3.4.1. The 105 control group companies are matched with 5 387 regular borrowers. Although the control sample is reduced by 21 observations, we do not believe the reduction would reduce model efficiency too much.

In table 4.3 we summarize the reduction in sample size from 645 to 105 due to missing SSIN numbers, -records, -values, outliers, and the CEM procedure.

Table 4.3: Remaining observations after the different stages during the data preparation processs.

Stage	**Sample size**
Collected from Lendix and Credit.fr	645
Indentified SSIN number	475
Records in the Amadeus database	332
After removing outliers and missing values	125
After CEM	105

We are as a result only working with a sample of 105 out of our intitial sample of 645 crowdlending borrowers.

4.4 Descriptive statistics

To better understand our data, and how it is distributed, we will present a series of descriptive statistics. Summary statistics on relevant credit ratios and credit scores are presented on the next two pages. In the following sections we will look at central characteristics of the sample, such as industry, year borrowed, region and age.

4.4.1 Summary statistics

In table 4.4.1.1 and 4.4.1.2, we present a series of summary statistics for our samples.

Table 4.4.1.1: Summary statistics for control group

Control group				Credit scores				Key credit ratios			
Industries	**Average / SD**	**Sample size**	**Age**	**Altman Z-score**	**Altman Sabato**	**Keasey McGuinnes**	**Gloubos Gramatikos**	**Working Capital / Total assets**	**Equity Total liabilities**	**EBIDTA / Total Assets**	**EBIDTA / Current liabilities**
Administration	Average	134	18,4	7,91	58,20	0,40	2,48	0,26	1,18	0,14	0,37
	SD		*8,4*	*2,17*	*6,81*	*0,60*	*2,53*	*0,19*	*1,34*	*0,10*	*0,37*
Construction	Average	893	20,0	8,19	57,90	1,05	2,61	0,31	1,06	0,12	0,30
	SD		*11,4*	*2,02*	*6,86*	*0,81*	*1,87*	*0,21*	*0,95*	*0,10*	*0,38*
Education	Average	6	17,0	8,71	56,74	0,05	2,61	0,43	0,77	0,14	0,33
	SD		*3,5*	*1,44*	*7,60*	*0,15*	*2,53*	*0,13*	*0,33*	*0,14*	*0,31*
Entertainment	Average	6	25,3	6,19	53,05	0,37	1,59	0,09	1,01	0,10	0,35
	SD		*16,1*	*1,88*	*7,04*	*0,52*	*4,08*	*0,19*	*1,17*	*0,10*	*0,26*
Information	Average	18	26,8	6,09	54,75	0,16	2,39	0,08	1,19	0,09	0,29
	SD		*13,4*	*3,35*	*13,10*	*0,29*	*3,67*	*0,14*	*2,13*	*0,09*	*0,50*
Manufacturing	Average	274	24,0	7,91	57,57	0,83	2,73	0,21	1,33	0,13	0,39
	SD		*14,0*	*2,43*	*6,53*	*0,72*	*1,94*	*0,21*	*1,46*	*0,09*	*0,35*
Retail	Average	2 630	20,3	7,48	55,86	1,73	2,51	0,20	1,16	0,11	0,33
	SD		*11,5*	*2,54*	*6,54*	*1,27*	*1,84*	*0,23*	*1,30*	*0,08*	*0,35*
Science	Average	128	19,5	7,73	57,79	0,48	2,62	0,26	1,06	0,13	0,33
	SD		*9,1*	*2,41*	*6,17*	*0,84*	*1,81*	*0,21*	*1,27*	*0,09*	*0,43*
Transport	Average	1 298	14,7	5,73	56,37	1,59	3,09	- 0,06	1,09	0,15	0,51
	SD		*9,9*	*2,44*	*6,16*	*1,37*	*1,91*	*0,11*	*1,35*	*0,11*	*0,53*
Average		5 387	19,1	7,21	56,50	1,46	2,68	0,16	1,13	0,12	0,37

Table 4.4.1.2: Summary statistics for treatment group

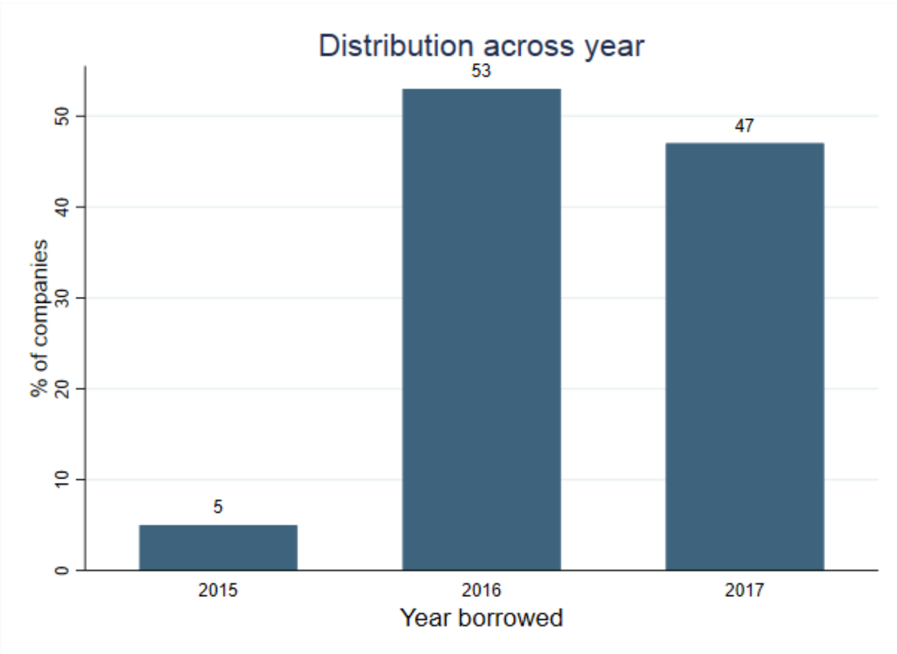
Treatment group				Credit scores				Key credit ratios			
Industries	**Average / SD**	**Sample size**	**Age**	**Altman Z-score**	**Altman Sabato**	**Keasey McGuinnes**	**Gloubos Gramatikos**	**Working Capital / Total assets**	**Equity Total liabilities**	**EBIDTA / Total Assets**	**EBIDTA / Current liabilities**
Administration	Average	7	15,0	5,43	50,88	0,24	2,61	0,19	0,23	0,10	0,16
	SD		*11,9*	*2,11*	*3,16*	*0,30*	*1,85*	*0,25*	*0,15*	*0,05*	*0,08*
Construction	Average	11	21,3	6,93	52,27	0,54	2,93	0,29	0,49	0,11	0,18
	SD		*16,7*	*1,35*	*3,32*	*0,59*	*1,60*	*0,15*	*0,34*	*0,07*	*0,11*
Education	Average	1	12,0	5,92	49,90	- 0,08	4,12	0,29	0,25	0,11	0,14
	SD			-	-	-	-	-	-	-	-
Entertainment	Average	4	33,3	5,99	53,04	0,01	3,07	0,21	0,43	0,11	0,23
	SD		*22,3*	*2,83*	*5,21*	*0,09*	*0,92*	*0,34*	*0,28*	*0,05*	*0,13*
Information	Average	7	17,1	5,23	51,45	0,18	2,85	0,02	0,66	0,09	0,15
	SD		*8,4*	*1,84*	*6,25*	*0,38*	*0,57*	*0,12*	*0,73*	*0,06*	*0,09*
Manufacturing	Average	14	26,6	6,89	51,58	0,64	2,95	0,24	0,72	0,11	0,27
	SD		*12,7*	*2,20*	*6,42*	*0,67*	*1,25*	*0,27*	*0,50*	*0,05*	*0,15*
Retail	Average	36	15,7	6,74	52,68	1,44	2,73	0,24	0,58	0,11	0,24
	SD		*13,2*	*2,23*	*5,37*	*1,65*	*1,39*	*0,27*	*0,66*	*0,05*	*0,27*
Science	Average	10	9,6	8,29	53,60	0,18	3,55	0,39	0,67	0,17	0,35
	SD		*5,3*	*2,07*	*5,72*	*0,40*	*1,09*	*0,23*	*0,39*	*0,11*	*0,24*
Transport	Average	15	14,2	5,54	52,12	0,85	3,92	- 0,03	0,84	0,18	0,57
	SD		*14,8*	*2,43*	*6,79*	*1,05*	*3,33*	*0,11*	*1,14*	*0,10*	*0,67*
Average		105	17,6	6,53	52,28	0,80	3,06	0,20	0,61	0,12	0,28

From the tables it is worth noting that the samples do not have large differences in standard deviations, despite the treatment group having relatively few observations within each industry. This could indicate that we have successfully removed outliers that could have greatly affected both standard deviations and the credit scores themselves. On average the crowdlending borrowers seem to have a smaller average credit score than the regular borrowers, except for the Gloubos Grammatikos model scores. In section 5 we will further elaborate on and analyze these differences.

4.4.2 Year borrowed

The number of observations for each year can be seen in figure 4.4.1.1. Both platforms, included in our study, Credit.fr and Lendix, were started in 2015, which explains the relatively low volume in that year. Although number of borrowers actually increased from 2016 to 2017, our dataset does not mirror this development. The Amadeus database contains few company records from 2016, the accounting year that we would have applied to represent loans originated in 2017.

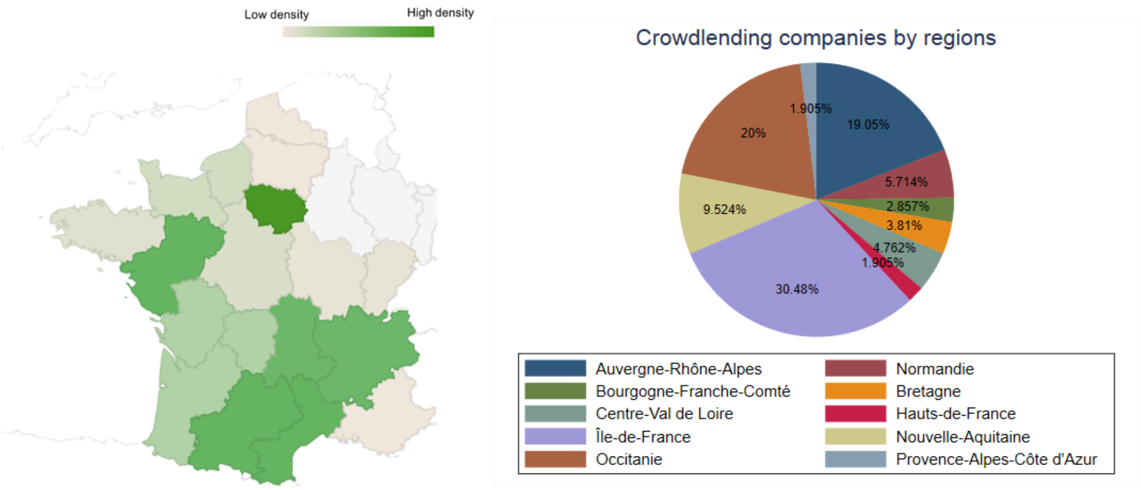
Figure 4.4.2.1 Distribution of crowdlending borrowers across the year they have borrowed.



4.4.3 Location

Crowdlending is a nation wide service in France. From the heatmap below we see that the number of borrowers is highly concentrated in Paris and the South-Eastern part of France. From the pie chart in figure 4.4.3.1 we see that Occitanie, Auvergne-Rhóne-Alpes and Ile-de-France (Paris) are well represented. Regions surrounding Ile-de-France, the North-East of France, and Province-Alpes-Cote d'Azur (region of Nice and Cannes) constitute smaller fractions of our sample.

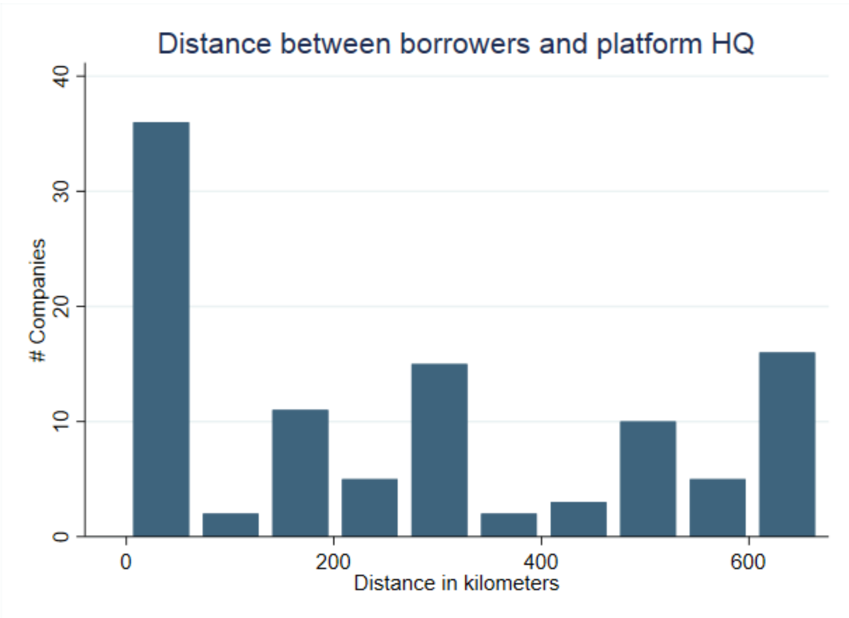
Figure 4.4.3.1 Heat map showing density of crowdlending borrowers across France and pie chart showing the geographical distribution of the same companies.



From figure 4.4.3.2 we see that most companies are located close to the platforms headquarters (Paris). As discussed in section 2.3, banks tend to lend more easily to companies which are situated close to the bank's headquarter. This could explain why we see so many borrowers situated in Paris, which is where the headquarters of both Lendix and Credit.fr are situated. If we exclude the Paris region (Ile-de-France), the distribution of distance to headquarter seem to be quite evenly spread out. This is somewhat opposed to the relationship banking litterature discussed in section 2.3, which would suggest a higher concentration in the Paris' neighboring. However, considering the small size of the crowdlending platform portfolios, this distribution can be greatly affected by one off events such as targeted marketing towards a specific region.

As the platforms are online only, without any branch infrastructure, it is easier for companies situated far away from the platform headquarters to apply for credit. This could also help explain the unsystematic geographic distribution.

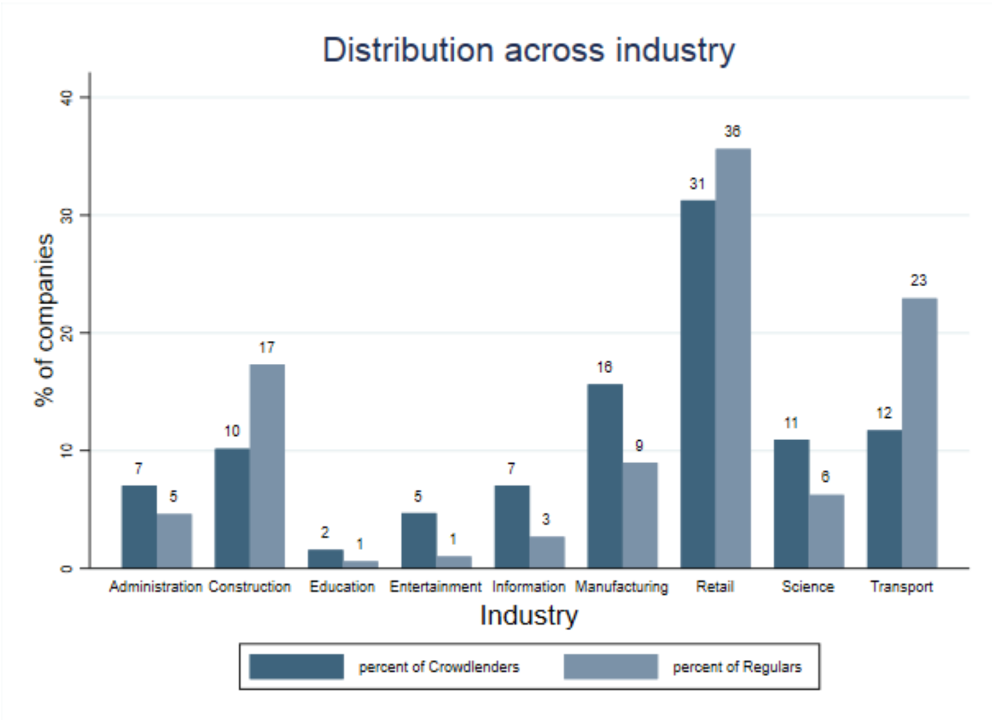
Figure 4.4.3.2 Distance from crowdlending platforms company headquarters and crowdlending borrower



4.4.4 Industry

From figure 4.4.4, we can see that crowdlending borrowers are often within wholesale, accomodation, construction and manufacturing. In our control group of regular borrowers we observe somewhat similar distribuitons, although the manufacturing-, science- and information industries have a higher representation on crowdlending platforms.

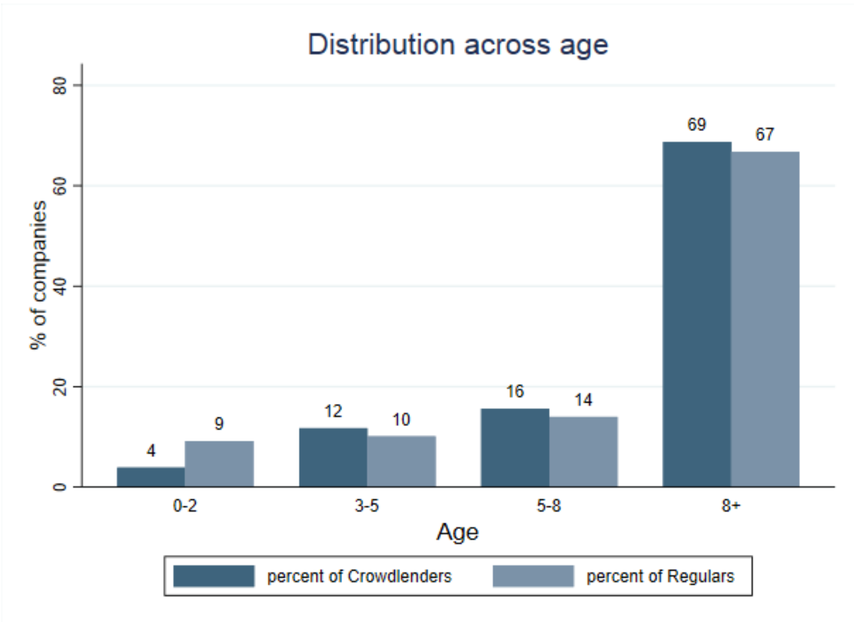
Figure 4.4.4: Industry representation across crowdlending borrowers and regular borrowers.



4.4.5 Age

From our sample, we see that most companies are quite mature. Most are eight years or older, while we see relatively few startups or young companies. This could be a suprising result as crowdfunding, of which crowdlending is a category, traditionally have been associated with startups. When it comes to crowdlending, plattforms are in fact able to attract borrowers that are both mature and as shown in the table from appendix 9.1, often have raised debt from financial institutions prior to borrowing through crowdlending.

Table 4.4.5 Age-group distribution in percentage within four categories in crowdlending sample



5. Empirical results

In this section, we will display the results we get from our four selected models, and compare them between our treatment and control groups. In section 5.1, we will compare the distribution of scores, together with making comparisons across industry, age and region. This will provide insight for creditworthiness and uncover potential blind spots for crowdlending platforms. Examples of such blind spots could be specific industries. We will also provide results from regressions, where the aim is to make causal inference regarding the credit quality of crowdlending borrowers. In section 5.2, we will analyze the cut-off scores for each credit model, and the share of companies in high likelihood of defualt. Furthermore, we will analyze individual credit ratios in section 5.3. In section 5.4, we will convert the Z''-scores to corresponding bond ratings, which will make it possible to compare the risk profile of the platform portfolios with regular bonds.

5.1 Credit scores

To gain insights into the general characteristic of the model results, we will present key statistics from each model. With QQ-plots we want to compare the score distributions between regular and crowdlending platform borrowers, we will also look at the differences in average scores across key covariates such as industry, age and region. Furthermore we will run regression analyses in order to see wether the differences in credit quality are significant across the two groups.

5.1.1 QQ-plots

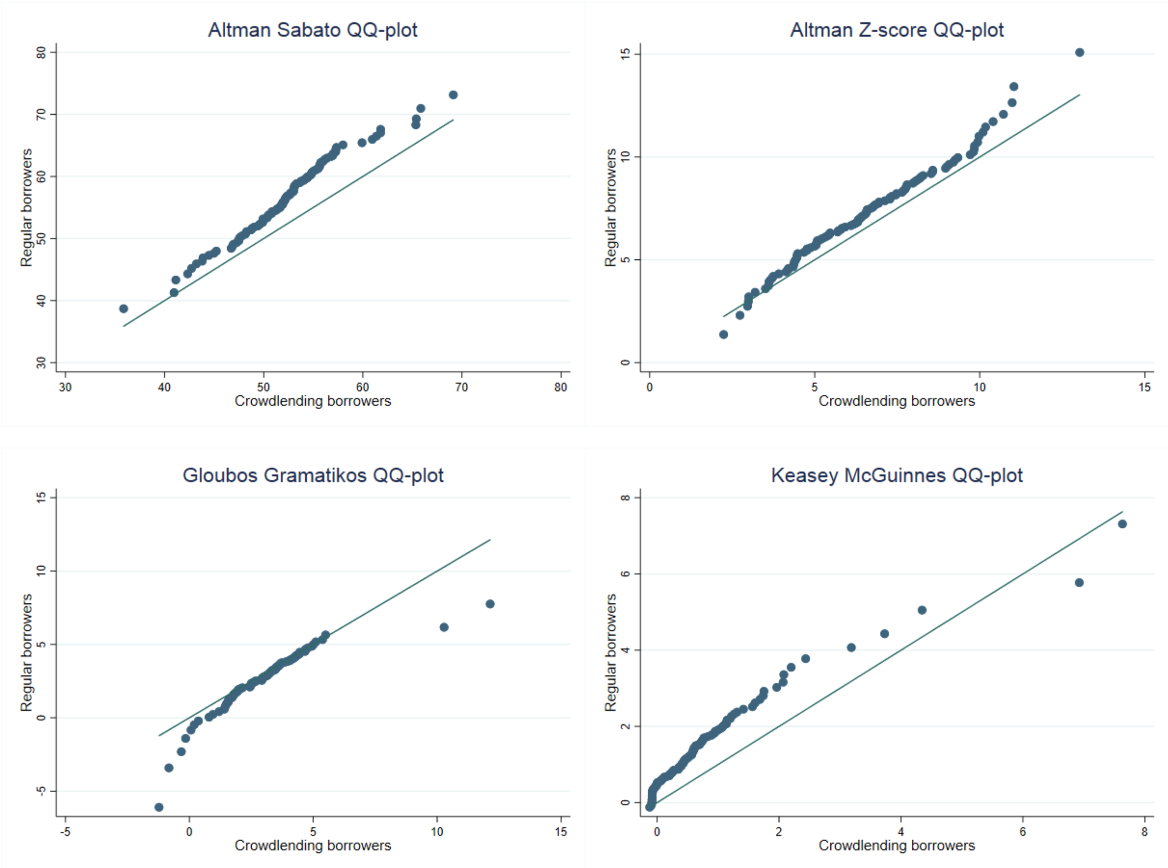
QQ-plots allow us to compare the distribution of credit scores between crowdlending borrowers and regular borrowers. This provides in depth insights into the underlying causes behind our regression results, which will be displayed in 5.1.6.

A quick look at the QQ-plots reveal that scores are in general skewed in favor of the regular borrower. This indicates that they have better credit scores than the crowdlending borrowers. The Altman Sabato model and the Keasey McGuinnes model have the clearest patterns. These models are also the two most recent models. The Keasey McGuinnes scores show consistently higher scores for regular borrowers, while the Altman Sabato model shows partiçulularly high scores for borrowers in the medium-high score range. The scores seem to even out towards the lower end of the plot. This could indicate that crowdlending platforms are as good as banks in avoiding low quality borrowers.

The Z''-score model tells a similar story as the Altman Sabato model. The distribution of scores between crowdlending borrowers and regulars is quite even, although slightly higher for regulars. Towards the lower part of the scale, the tail seems to tip slightly in favor of crowdlending borrowers. This further strenghtens our findings from the Keasey McGuinnes and Altman Sabato models.

The Gloubos Grammatikos model tells a different story from the other three credit models. From the QQ-plot we see that scores are quite similarly distributed in the higher range of the scale. In the lower end of the scale, the distribution is skewed clearly in favour of the crowdlending borrowers. Thus, the Gloubos Grammatikos qq-plot tells us that in general, there is little difference between banks and crowdlending platforms, but that crowdlending platforms are more restrictive when it comes to companies with poor credit scores.

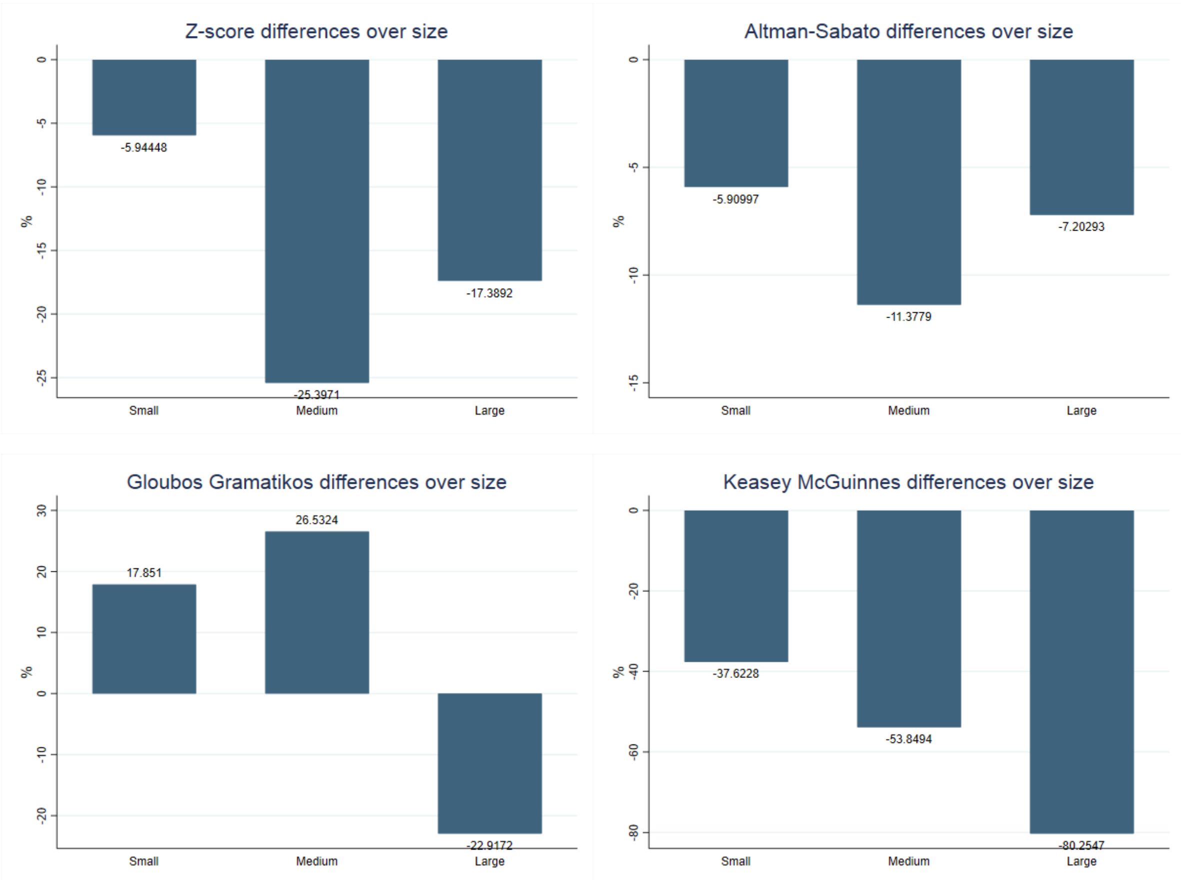
Figure 5.1.1 QQ-plot comparing distributions of credits scores between all models



5.1.2 Distribution across size

From figure 5.1.2 we see that crowdlending borrowers consistently maintain lower scores across all size groups, except for the Altman Sabato model where there is a marginal difference across size groups. In the Z''-score and Altman Sabato models, the medium sized crowdlending borrowers have on average lower credit scores. Amongst crowdlending borrowers, small companies seem to perform comparatively better than regular borrowers. When running t-tests on the differences between the samples, we find that medium sized crowdlending borrowers have significantly lower scores than medium sized regular borrowers across three out of four models. Large crowdlending borrowers also turn out to be significantly worse in the Keasey McGuinnes and Altman Sabato models. The complete t-test results can be found in appendix 9.6.1. This tells us that crowdlending platforms might have a weak spot when it comes to the riskiness of their medium sized borrowers.

Figure 5.1.2 Bar charts showing how much the crowdlending scores across size differ in percent compared to regular borrowers.



5.1.3 Distribution across industry

When running t-tests across all industries, we find that crowdlending borrowers are significantly worse in the construction industry across all models except the Gloubos Grammatikos model. Transport and administration show significantly lower results for crowdlending borrowers in two of the models. See appendix 9.6.2 for full t-test results.

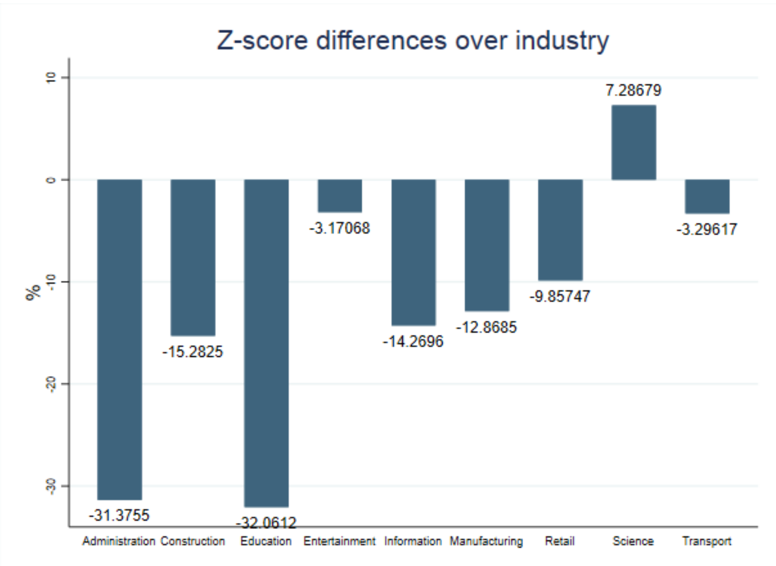
From figure 5.1.3, the same pattern is evident when looking at differences in % between crowdlending and regular borrowers. The credit scores for construction companies may be explained by the commonality of hard assets such as standardized machines. These assets are easy to value, it would give them a greater opportunity to obtain credit. In the same way, science companies often have expensive equipment although arguably with lower liquidity than construction equipment.

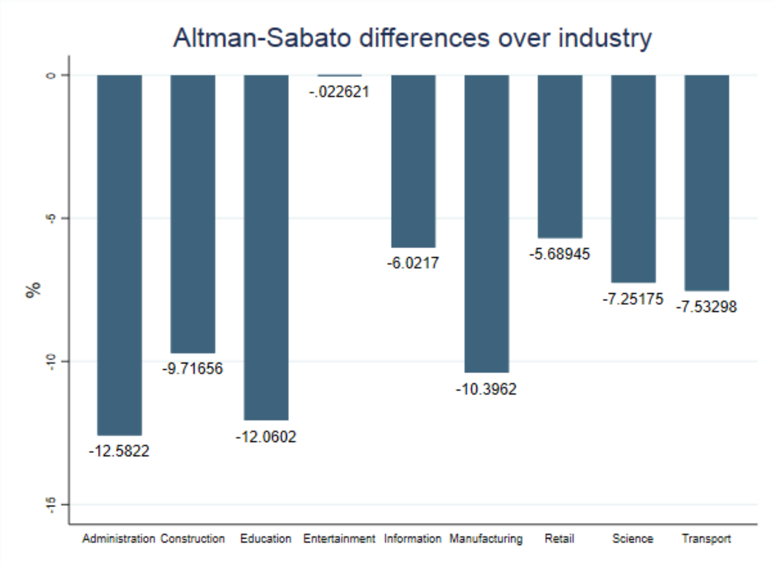
The relatively weaker scores of administration and science might also be an indication that crowdlending platforms value immaterial assets such as patents or human capital higher than banks.

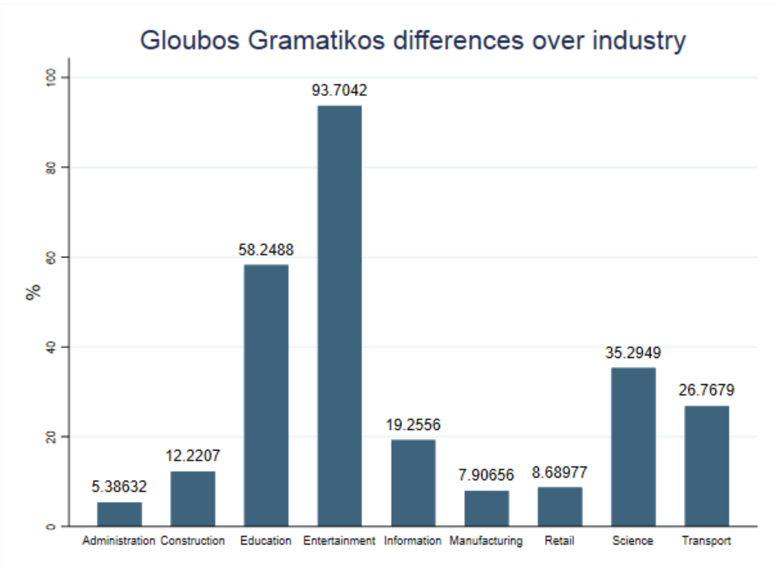
The Z''-score and Altman Sabato models have relatively lower differences in % between crowdlending borrowers and regular borrowers.

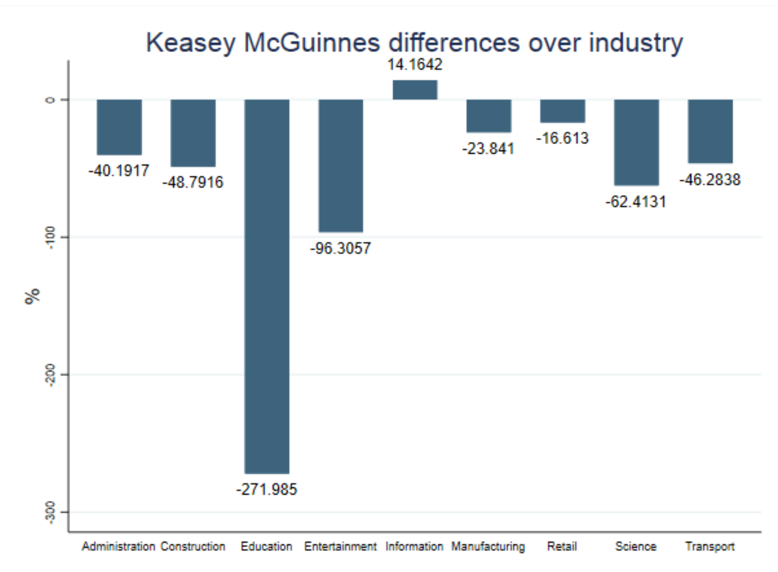
The crowdlending borrowers outperform regular borrowers in the Gloubos Grammaticos model, although no results are statistically significant. On the other hand, Keasey McGuinnes inherits the most variations across industries, and contains quite large negative gaps in favor of regular borrowers.

Figure 5.1.3 Bar charts showing the how much the crowdlending scores acrosss industry differ in percent compared to regular borrowers.




Altman-Sabato differences over industry
%
0
-5
-10
-15
-12.5822
-9.71656
-12.0602
-.022621
-6.0217
-10.3962
-5.68945
-7.25175
-7.53298
Administration
Construction
Education
Entertainment
Information
Manufacturing
Retail
Science
Transport


Gloubos Gramatikos differences over industry
%
0
20
40
60
80
100
5.38632
12.2207
58.2488
93.7042
19.2556
7.90656
8.68977
35.2949
26.7679
Administration
Construction
Education
Entertainment
Information
Manufacturing
Retail
Science
Transport

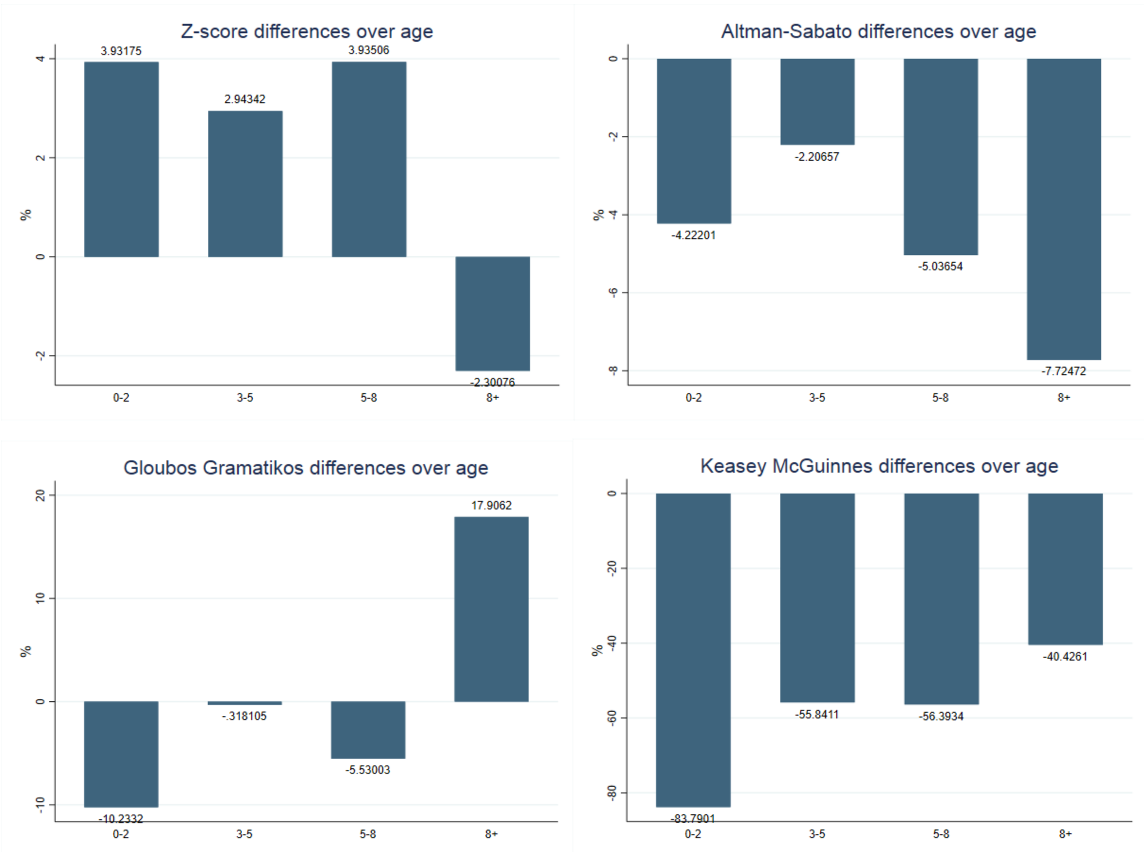

Keasey McGuinnes differences over industry
%
0
-100
-200
-300
-40.1917
-48.7916
-271.985
-96.3057
14.1642
-23.841
-16.613
-62.4131
-46.2838
Administration
Construction
Education
Entertainment
Information
Manufacturing
Retail
Science
Transport

5.1.4 Distribution across age groups

The crowdlending borrowers seem to do quite well compared to regular borrowers across the Gloubos Grammatikos and Z’’-score model. The results from the t-tests (appendix 9.6.3) indicate that only significant differences are the Keasey McGuinnes scores, and the age groups 5-8 and 8+ on the Altman Sabato model.

In the Keasey McGuinnes and Gloubos Grammatikos models, the crowdlending borrowers seem to improve compared to the regular borrowers as they mature. On the contrary, in the Altman Sabato model, credit score seems to improve with lower age. This pattern is also found in the Z’’-score model.

Figure 5.1.4 Bar charts showing the how much the crowdlending scores acorss age differ in percent compared to regular borrowers.



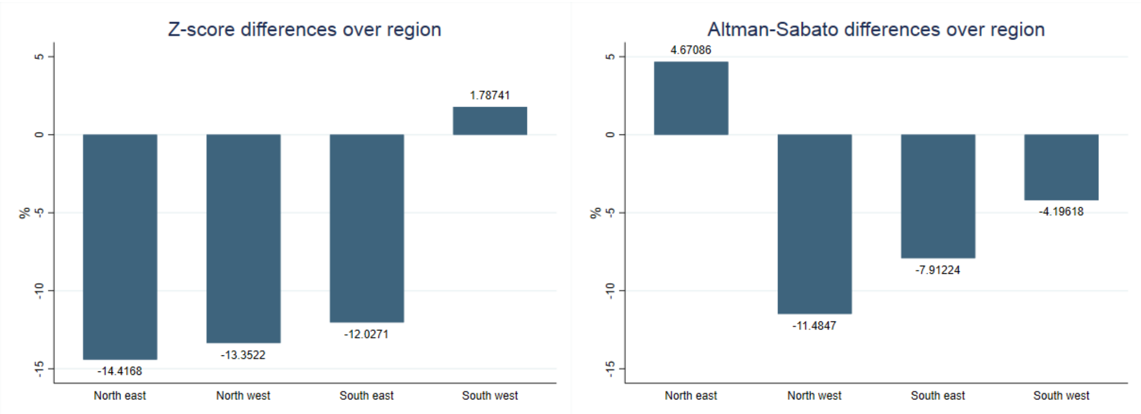
5.1.5 Distribution across region

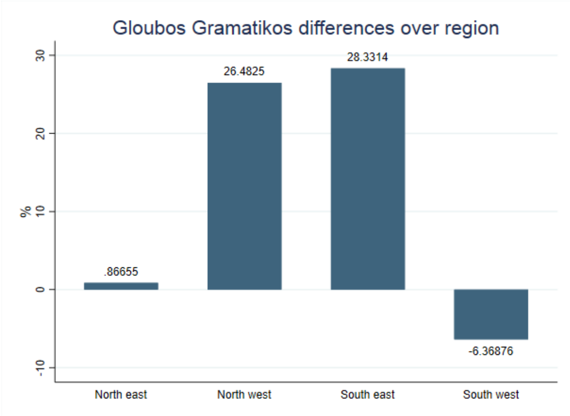
Across region, again, the general tendency seem to be a lower performance in credit scores for crowdlending borrowers. The t-test results provided in appendix 9.6.4 show that the differences in the north west region are significant across all models, while north east is significant in the Altman Sabato model, and south west is significant in the Altman Sabato and Keasey McGuinnes models. None of the models are significant across all regions.

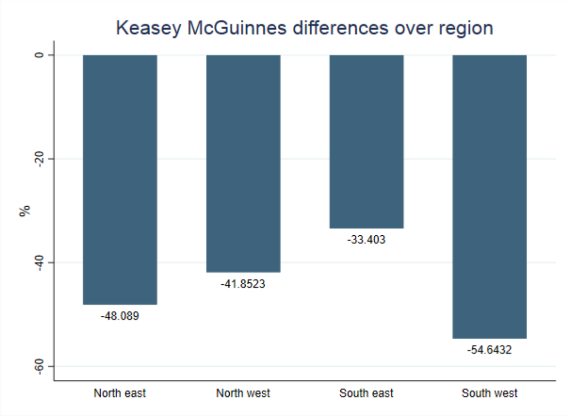
All models except the Gloubos Grammatikos model, suggest that crowdlending borrowers in general have lower credit scores.

In opposition to industry where difference in credit score performance is larger, it is hard to find particular weak spots across the regions. If anything, the crowdlending borrowers seem to have consistently worse credit scores in all regions. The relationship banking litterature discussed in section 2.3 suggest that banks are more lenient towards companies situated close to their headquarters (north west in our case). Our findings suggest no such pattern.

Figure 5.1.5 Bar charts showing the how much the crowdlending scores across size differ in percent compared to regular borrowers.







5.1.6 Regression outputs

The regression results in large tell the same story as the QQ-plots. For all models except for the Gloubos Grammatikos model, crowdlend has a negative coefficient, indicating that the credit score is on average lower for companies that lend through crowdlending platforms. From figure 5.1.6, we see that only the Altman Sabato and the Keasey McGuinnes model yield significant results. The Gloubos Grammatikos model is the only model to indicate a higher creditworthiness for crowdlending borrowers, but the results are not significant. This suggests that crowdlending borrowers have a lower credit score than regular borrowers. Previous studies and findings discussed in section 3.3 suggest that crowdlending borrowers have a higher LGD and lower collateral. Thus, all evidence suggest that crowdlending borrowers have a lower credit quality than regular borrowers.

Figure 5.1.6 Regression on the four credit score models, independent variable is the binary value *"Crowdlend" 1=Crowdlend, and 0=Regular*. The dependant variable is credit score. The statistical models used is further discussed in section 3.4.

	Altman Sabato	Z''-score	Gloubos Grammatikos	Keasey McGuinnes
crowdlend	-4.372^{**}	-0.679	0.390	-0.708^{**}
	(0.001)	(0.204)	(0.319)	(0.006)
_cons	56.66^{***}	7.214^{***}	2.665^{***}	1.510^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
N	5492	5492	5492	5492

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

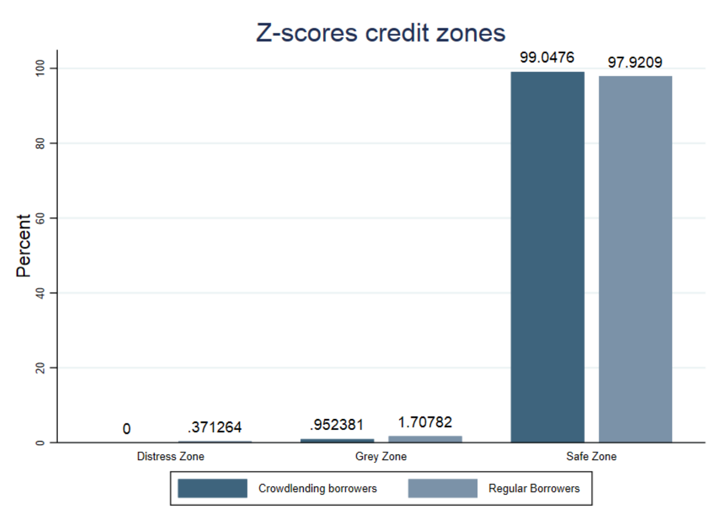
5.2 Companies below cut-off or in distress zones

All models except the Altman Sabato model operate with cut-off scores which indicate the treshhold for high likelihood of defaulting. Across all models, a company below the cut-off score is predicted to go bankrupt within one year. Analyzing these cut-off scores indicate how poor credit quality the platforms are willing to accept. In the following sections we will present descriptive statistics outlining the general distribution of companies below cut-off. We will also provide regressions which give insights into whether the crowdlending platforms have unusually high proportions of companies below cut-off.

5.2.1 Descriptive statistics

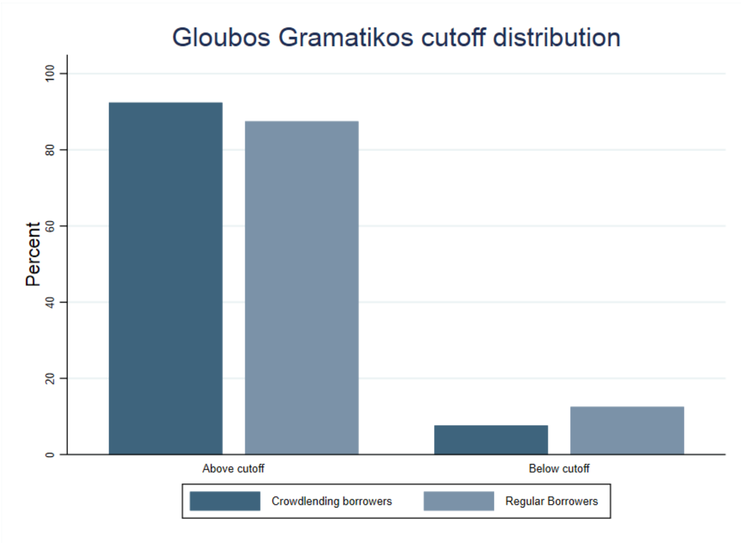
The Z''-score model operates with three zones: "Distress Zone", "Grey Zone" and "Safe Zone". Figure 5.2.1 illustrate the distribution across the three zones. Few companies are located in the grey- or distress zone. More than 99% of the crowdlending borrowers and about 98% of the regular borrowers are in the safe zone. This is quite intuitive as one would expect default rates to be in the low single digits. For crowdlending borrowers, 10 companies are in the Grey Zone, interesting as platforms would have this information on the time of loan approval. Furthermore, we see the share of regular borrowers in the grey zone being twice the size compared to crowdlending borrowers.

Figure 5.2.1 Distribution of crowdlending and regular borrowers across Z''-score zones.



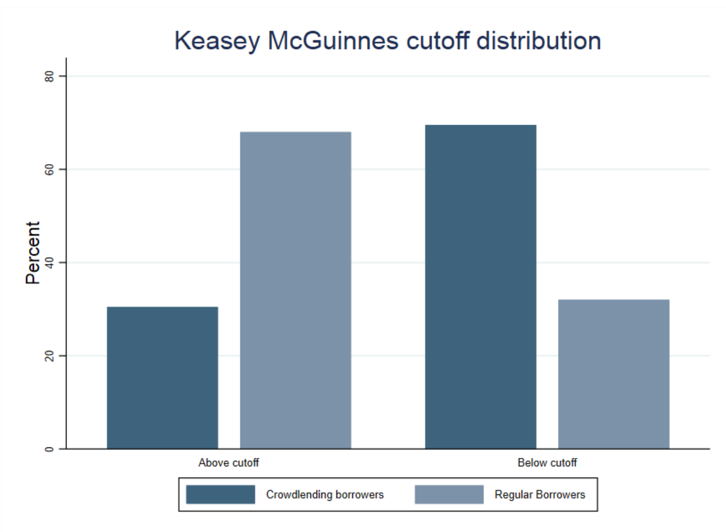
The Gloubos Grammatikos model operates with a simple cut-off rate, instead of zones. From figure 5.2.2 we see that a smaller percentage of crowdlending borrowers are below the cut-off score, indicating that fewer crowdlending borrowers are in serious risk of default to that of regular borrowers. The total share of predicted defaults is higher than the Z''-score model, but still in a single digit territory.

Figure 5.2.2 Distribution of crowdlending and regular borrowers across Gloubos Grammatikos cut-off scores



Most of the crowdlending borrowers are below the cut-off score for the Keasey McGuinnes model. This is different from the Z’’-score and the Gloubos Grammatikos models. This seems counter intuitive, and might suggest that the cut-off score is not entirely accurate when applied to our sample. The original Keasey McGuinnes (1990) article does not operate with a cut-off score, we rely on one estimated by Ooghe and Balcaen (2007). The regular borrowers have an abnormally high proportion of companies below the cut-off score as well, indicating default rates of more than 30% across the French population of companies.

Model 5.2.3 Distribution of crowdlending and regular borrowers across Keasey McGuinnes cut-off scores



5.2.2 Regression outputs

To see whether crowdlending platforms have a significant difference in share of companies below the cut-off scores, we perform a series of regressions. In the regressions we rely on the dependent variable above or below cut-off, where 0 means below and 1 means above. The independent variable is "crowdlend", where 0 means regular borrower and 1 means crowdlending borrower. Thus, a positive slope coefficient would indicate that a higher share of crowdlending borrowers are above cut-off.

First, we regress on the exact cut-off scores, before we increase the cut-off scores for the Z''-score and Gloubos Grammatikos model by 10, 20 and 30 percent. We reduce cut-off scores by the same intervals in the Keasey McGuinnes model since it indicates a too high cut-off score.

Table 5.2.4: Regression results against cut-off scores ranging from exact cut-off scores, to cut-off scores with increased (decreased) by up to 30%. * Denotes significance level where $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. (+) and (–) indicates the slope of the coefficient which is the binary variable "crowdlend", where 1 = crowdlending borrower and 0 = regular borrower. The dependent variable is a binary variable, where 1 = above cut-off and 0 = below cut-off. A positive slope coefficient will thus indicate a higher share of crowdlending borrowers above cut-off. Actual cutoff scores can be found in appendix 9.7.

Regression results

Distance from cut-off	Keasey McGuinnes[1]	Gloubos Grammatikos[2]	Z'' - score[2]
0 %	(–)***	(+)	(+)
–10%[1] & + 10%[2]	(–)***	(+)	(+)**
–20%[1] & + 20%[2]	(–)***	(+)**	(+)***
–30%[1] & + 30%[2]	(–)***	(+)	(+)***

From table 5.2.4 we see that the Keasey McGuinnes model is the only significant throughout all regressions. The results indicate that crowdlending borrowers are more likely to be below cut-off, and in high risk of default, than regular borrowers. The Gloubos Grammatikos model and Z''-score model indicate the opposite, but the results are not significant.

When adding 10% to the cut-off scores in the Z''-score and Gloubos Grammatikos, and subtracting 10% from the Keasey McGuinnes, we see that the general picture has not changed by much. This time the Z''-score shows a significant result, indicating that crowdlending borrowers are less likely to be below the cut-off point + 10 percent. This tells the opposite story of the Keasey McGuinnes model, though the size of the crowdlend coefficient indicate a small effect.

When adding or subtracting 20%, we get significant results for all three models. Both the Gloubos Grammatikos model and the Z''-score model indicates that crowdlending borrowers have a lower probability of being below the cut-off + 20% range. The Keasey McGuinnes model tells the opposite story. The coefficient in the Gloubos Grammatikos model indicates a larger effect than the Z''-score model.

When adding and subtracting 30% we lose the statistical significance of the Gloubos Grammatikos model. The size of the Z''-score coefficient has also increased slightly.

The Keasey McGuinnes model consistently suggest that crowdlending platforms have a high share of low quality borrowers. The Gloubos Grammatikos and the Z''-score model suggest the opposite, though not always with significant results. The Z''-score is significant for all cut-off points that are set 10%, or more, above the original. The regression results are quite robust when testing for different percentage slack, however with differing levels of significance.

Although the models contradict each other, we find it natural to place more faith in the Gloubos Gramatikos and Z''-score results. Both models display credible proportions of companies under cut-off, while the Keasey McGuinnes results seem a bit high. We therefore suggest that crowdlending platforms are less likely to be below or close to the cut-off score. In section 5.1, we show how crowdlending borrowers have a lower credit quality than regular borrowers. These findings nuance the picture somewhat. We can conclude that despite having lower quality, crowdlending platforms still avoid the most risky borrowers.

5.3 Credit Ratios

The credit scoring models consist of various credit ratios. Credit ratios are an important part of any credit model, and analysing them on their own can give insights to both credit quality and also identify potential weak spots. Out of 14 individual credit ratios, we get significant results on four, which are displayed in table 5.3.0. For a comprehensive list of all credit ratios, see appendix 9.4.

Across the four models, only three credit ratios are featured in more than one model. Two of these ratios, equity over total liabilities and retained earnings over total assets, display significant results. In the following sections, we will discuss the individual results for the significant ratios, and how they describe a company's credit score.

Table 5.3.0: Credit ratios with significant results. Independent variable is the binary value "Crowdlend", where 1 = Crowdlend and 0 = Regular. The dependant variable is the credit ratio.

	Equity/Total Liabilities	**Creditors Turnover**	**Retained Earning/Total Assets**	**Cash/Total Assets**	**Current Ratio**
crowdlend	-0.576***	-2.683**	-0.134**	-0.0988***	-0.280***
	(0.000)	(0.005)	(0.003)	(0.000)	(0.000)
_cons	1.186***	5.978***	0.361***	0.173***	1.613***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	5492	5492	5492	5492	5492

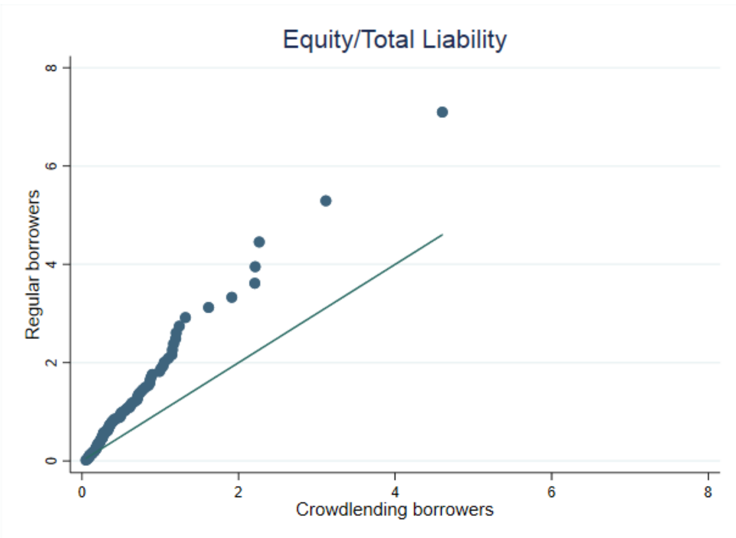
p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3.1 Leverage

The equity over total liabilities ratio is a leverage measure. Thus, the negative slope coefficient of crowdlend indicates that crowdlending borrowers are more leveraged than regular borrowers, by having a lower equity relative to total liabilities. This ratio is an important part of both the Z''-score model and the Keasey McGuinnes model, and can explain some of the findings. From the QQ-plot in figure 5.3.1 below, we see that regular borrowers generally are less leveraged, even at the lower tail of the scale. This could indicate that crowdlending platforms tend to grant loans to companies that have exhausted their other financing options, which we will discuss further in section 6.3.1 on loan terms.

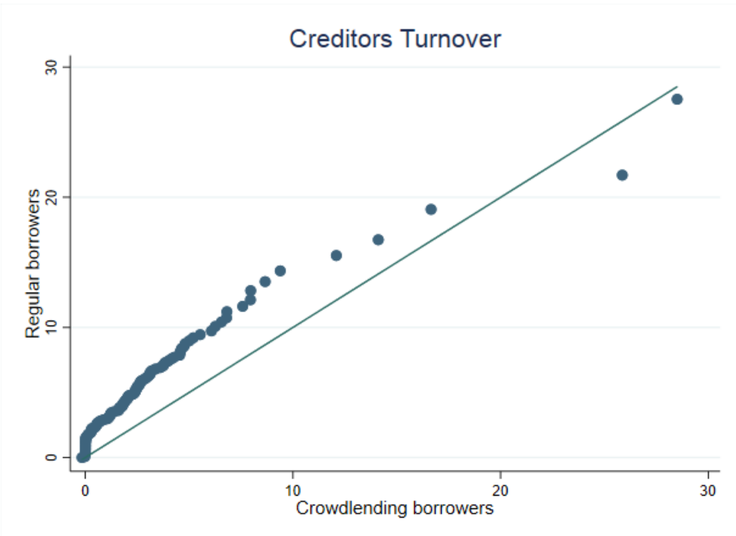
Figure 5.3.1 QQ-plot displaying the Equity/Total liability ratio.



5.3.2 Creditors turnover

From the regression, we see that crowdlending borrowers have a lower creditors turnover ratio than regular borrowers. The creditors turnover ratio, or accounts payable turnover ratio, measures the speed in which a company repay debt to its suppliers. Thus, a lower ratio can mean two things: the company has a poor liquidity, or it enjoys a good credit standing with its creditors. In the Keasey McGuinnes model, a higher ratio indicates lower risk of default. From the regression we see that crowdlending borrowers have a poorer creditors turnover ratio than regular borrowers. This tells us that their liquidity is lower, which in turn could be why they are turning to crowdlending platforms which often operate with short term loans spanning some months or a few years.

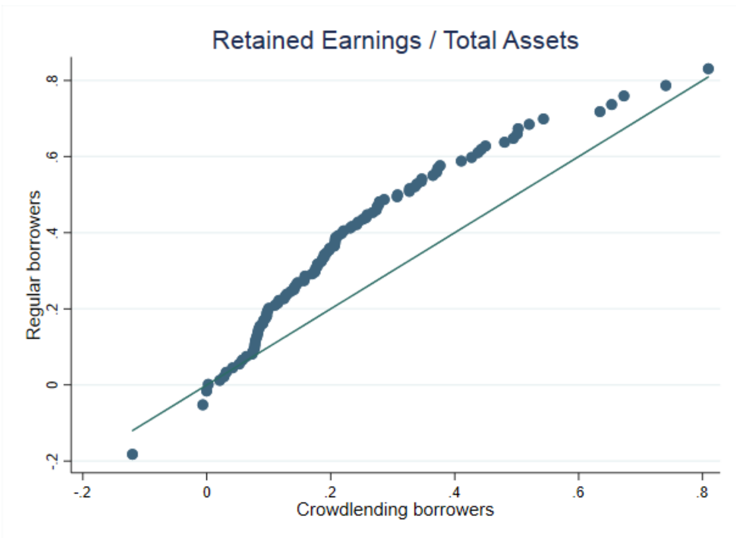
Figure 5.3.2 QQ-plot displaying the creditors turnover ratio.



5.3.3 Profitability

The retained earnings over total assets ratio is a widely applied measure of historic probability, and figures both in the Altman Sabato model and the Z''-score model. The results from the regression and the QQ-plot in figure 5.3.3 below suggest that regular borrowers in general are more profitable than crowdlending borrowers. It could also indicate that crowdlending borrowers have historically paid more dividends, thus not reinvesting their retained earnings to generate future growth. When considering the pecking order theory, a lower ratio due to dividend allocation could be a warning sign that crowdlending borrowers are not financing efficiently. The distributions are normalized at the tails.

Figure 5.3.3 QQ-plot displaying the Retained Earnings/Total Assets ratio.

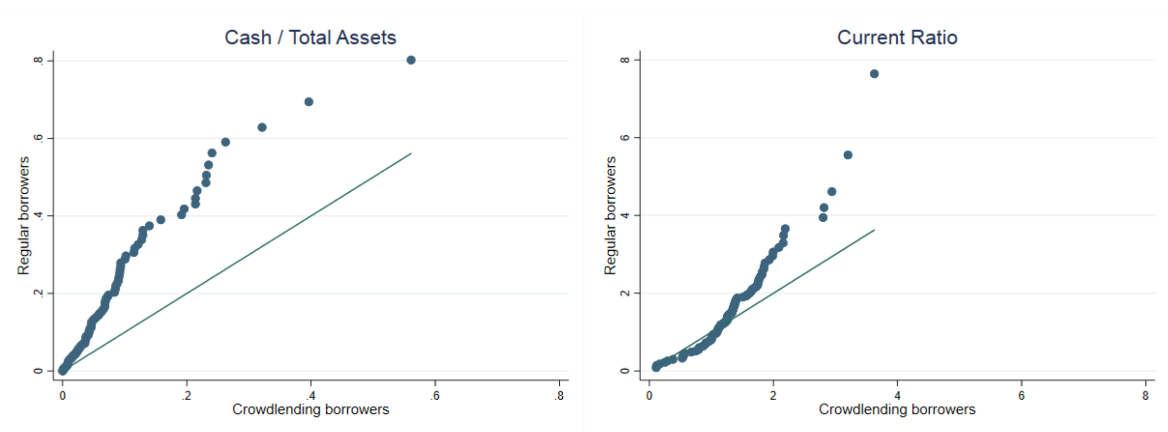


5.3.4 Liquidity

Cash over total assets is a liquidity ratio. It features in the Altman Sabato model. The results from the regression and the QQ-plot in figure 5.3.4 below suggest a significant difference in distributions where crowdlending borrowers have a lower ratio and thus worse liquidity. This means that crowdlending borrowers are more sensitive to liquidity shocks. It could also be a reason for why they are seeking refinancing.

Current ratio is current assets over current liabilities, and is considered a liquidity measure indicating ability of fulfilling the company's short term obligations. It features in the Gloubos Grammatikos model where a high current ratio indicates a lower score. A high current ratio is a sign that the company is not utilizing its short-term debt facilities, or that suppliers and banks are not willing to provide the company with short term credit. In the regression model, we see that crowdlending borrowers have lower current ratios than regular borrowers, which could explain some of the results we see in the Gloubos Grammatikos model overall. From the QQ-plot we see that crowdlending borrowers actually have higher current ratios in the lower end of the scale, but lower current ratios in the high end of the scale. This could indicate that more crowdlending borrowers are in a zone where they have access to short term debt, without being over-leveraged.

Figure 5.3.4 QQ-plot displaying the significant liquidity ratios.

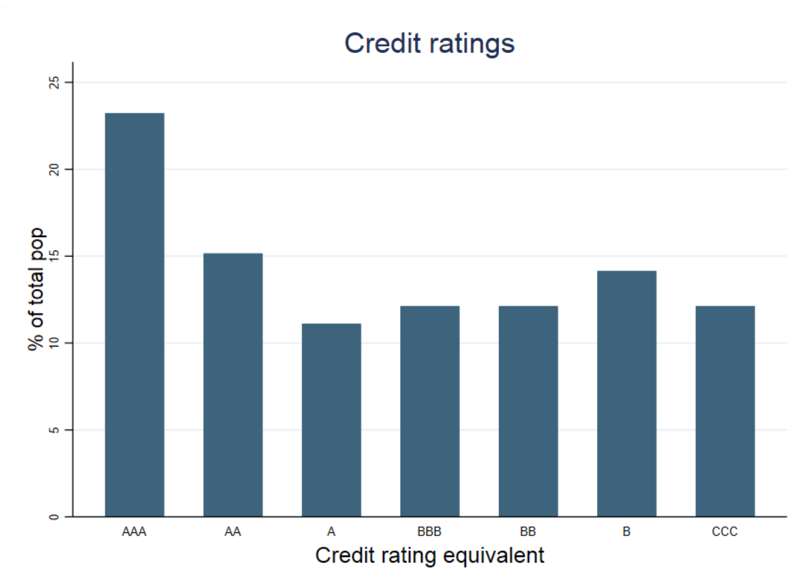


5.4 Credit rating equivalents and interest rate

Altman Z''-scores can be converted into credit rating equivalents, using a conversion chart provided by Altman and Rotblut (2016), where he benchmarks Z''-scores against bond ratings. This provides a rating proxy. The letter grades from credit ratings are widely acknowledged, and easy to understand. Thus, this exercise provide an easier to understand picture of how the credit quality is distributed in our sample.

From figure 5.4.0 we see that there is a high proportion of companies with triple A rating equivalents (none are actually rated by rating agencies), and on lower credit ratings the companies are more evenly distributed. This indicates that crowdlending platforms attract high quality borrowers, while also catering to the lower ends of the market. According to the ratios, 60% of the borrowers are characterized as "investment grade" (above BBB), while 40% are characterized as "high yield" (below BBB) (Altman & Rotblut, 2016).

Figure 5.4.0 Distribution of credit rating equivalents, following the conversion process discussed in the above section.



In table 5.4.1 we see the corresponding interest rate characteristics from our sample, to credit rating equivalents. The interest rate seems to be quite independent of the credit rating. This can be due to a small sample size, higher collateral requirements for lower rated companies, or other loan terms that regulate loss given default (LGD) and thus the actual risk of each loan. The statistics indicate that crowdlending platforms are asking an interest in certain intervals across all loans, and mainly between 6-7%.

Table 5.4.1: Credit rating equivalents and corresponding interest rates based on the Z''-scores and Altman's conversion chart (2016)

Credit rating equivalents	**Share of population**	**Avg interest rate**	**Median interest rate**	**Min interest rate**	**Max interest rate**
AAA	23%	7.19%	6.65%	6.0%	8.1%
AA	15%	6.69%	6.6%	4.6%	9%
A	11%	6.91%	7.5%	4.75%	9%
BBB	12%	7.25%	7.5%	6.0%	8.5%
BB	12%	6.73%	6.13%	4.75%	8.8%
B	14%	7.27%	7.5%	6.0%	8.5%
CCC	12%	7.13%	7.35%	5.0%	8.7%
D	0%	-	-	-	-

6. Discussion

In this section, we will discuss our empirical findings and their implications with regards to the theories presented in section 2.

6.1 Analyzing credit scores

From all models except the Gloubos Grammatikos model, we observe lower credit scores for companies borrowing through crowdlending platforms, than regular borrowers. In two of the models, the results are significant. In section 5.1.6 we conclude that crowdlending borrowers have lower credit quality than regular borrowers. This could mean that crowdlending platforms are exposed to the adverse selection effects that come from having high interest rates, or from the switching costs associated with change of lender. It could also mean that the platforms intentionally target borrowers due to a potential gap in the SME financing market, caused by a significant credit tightening following the financial crisis and Basel III regulations.

6.1.1 Adverse selection

The differences in credit scores may be a consequence of adverse selection. As mentioned in section 2.3, banks engage in relationship banking and use the information, harnessed from the relationship, in their credit evaluation. This means the insider bank accumulates superior information, which enables them to evaluate credit risk better than outsider banks.

Documented cosequences of relationship banking are high switching costs, which would make it difficult for outsider banks to poach customers (Kliger & Vale, 2003). In addition, it has been shown that in times of economic expansion, the credit quality amongst borrowers that switch lenders tend to be worse (Hetland & Mjøs, 2012). The platforms in our research have been active since 2015. They have only experienced times of economic expansion, and are unlikely to have formed solid relationships with their borrowers. It is thus reasonable to assume that crowdlending platforms face adverse selection problems, attracting companies looking to extend credit or improve loan conditions.

From our findings, we see a clear pattern of companies with lower credit scores borrowing from crowdlending platforms. Still, as shown in appendix 9.1, almost all companies in our sample of crowdlending borrowers have long term debt to other financial institutions. This indicates a history of participating in a lending relationship. The companies could have switched to crowdlending for extended credit, lower interest rates, or less collateral requirements.

When benchmarking the average interest rate against the ICE Bank of America Merrill Lynch Euro High Yield Index, we find a positive average spread of about 3% in favour of crowdlending platforms (Federal Reserve Bank of St. Louis, 2018). When converting Z''-scores to credit rating equivalents in 5.4, we find that crowdlending platforms contain 60% investment grade, and only 40% high yield borrowers. Benchmarking against the high yield index is thus a conservative approach. There can be multiple explanations for the spread. Most high yield bonds are liquid, while neither Lendix (2018) nor Credit.fr (2018) facilitate 2nd hand markets. Thus investments through these platforms must incorporate a liquidity premium. Another explanation could be that the platforms are putting a high price on risk, in order to adjust for adverse selection effects. In this case, low interest rates would not be the sole reason for why borrowers switch to crowdlending platforms.

The size of credit granted, credit quality acceptance level, ease of applying and processing speed might be probable explanations. In a survey from FundingCircle, 31% of borrowers cite speed as their main reason for applying. Ease of applying comes second with 28.1% and 10,5% cite low interest rates as their main motivation for applying. Only 21% believe that they would not be able to secure financing elsewhere (Centre for Economics and Business Research, 2016). This could indicate that adverse selection does not impact crowdlending platforms too much. The findings also give support to the hypothesis that crowdlending borrowers are willing to accept higher interest rates than their risk profile would indicate, since interest rates are not their primary cited reason for going to crowdlending platforms.

Our results in section 5.3, show that crowdlending borrowers tend to be higher leveraged than regular borrowers, and have a weaker liquidity. This provides support for the theory that borrowers might choose crowdlending platforms to maintain or further increase their leverage, or alleviate short term liquidity issues through borrowing for working capital.

Another aspect of adverse selection is the interest rates that the platforms offer. Although they offer interest rates as low as 2,5%, the interest rates in our sample tend to average 7% despite varying credit scores. This could therefore suggest that crowdlending platforms aim for an average interest rate around 7%, in order to attract capital. Interest rates at this level discourage high quality borrowers.

6.1.2 Credit tightening and credit rationing theory

France is a relatively well banked country. However, Europe has experienced a tightening of credit following the financial crisis and Basel III regulations. The International Monetary Fund estimated the magnitude of the tightening at $2.6 trillion across European banks. This effect has been evident in the European high yield bond markets, which have grown by 500% between 2010 and 2015, offsetting some of the credit tightening effect for larger corporations. The tightening of credit suggest that the banks have found a new optimal interest rate. In accordance with credit rationing theory, they would not be willing to lend at rates above this level. SMEs rely on traditional banking, and lack access to bond markets, it is therefor reasonable to assume that the credit tightening has led to fewer borrowers with higher quality (Altman, Esentato, & Sabato, 2016).

The influx of new capital through crowdlending platforms could cause the credit markets for SMEs to loosen up. Another important observation is that crowdlending platforms have few capital requirements, and are not affected by the Basel III banking regulations. In this sense, the platforms have more in common with bond markets than banks, as discussed in section 2.2. This means that the crowdlending platforms do not have to offset a high average default rate accross their portfolio with extra capital reserves. This regulation may re-direct banks to deliberately target companies with high credit ratings, resulting in an underbanked segment of lower credit quality. Companies could be willing to accept a higher risk adjusted interest rate, and thus be an attractive segment for crowdlending platforms.

6.2 Analyzing cut-off rates

The cut-off rate regressions in section 5.2 show that the lower credit quality of the crowdlending portfolios do not necessarily translate to a higher proportion of companies in serious risk of default. Expanding on the analysis in the previous section, we analyze the cutoff results through credit rationing and asymmetric information theory.

6.2.1 Credit rationing theory and credit tightening

As discussed in the previous section, crowdlending platforms may deliberately target lower quality borrowers, due to a lower optimal interest rate in regular banks. By analysing cut-off rates, we can investigate whether the platforms have clear standards of what credit quality they will accept. If the platforms have unusually high proportions of borrowers in serious risk of default, this could be a symptom of poor or random credit evaluations.

From the QQ-plots in figure 5.1.1, we see how credit scores tend to increase for regular borrowers in the top tail, but stay at or below the mean in the lower tail. In other words, the proportion of "top" borrowers are higher amongst regular borrowers, while the proportion of "junk" borrowers is similar between crowdlending borrowers and regular borrowers. This is supported by our regressions in 5.2. In these, the Z''-score and Gloubos Grammatikos credit models indicate that crowdlending borrowers are less likely to be below or close to the cut-off score.

We find that few crowdlending borrowers are close to or below the cutoff scores, except for in the Keasey McGuinnes model. Combined with our regression results, this indicates that the platforms' performance are similar to banks' when it comes to rejecting companies with a high probability of default.

These results suggest that while crowdlending platforms are targeting companies with lower credit quality, they have clear preferences for how risky firms they will accept. The low proportion of crowdlending borrowers below cutoff scores and high proportion inside the "safe zone" support this argument. Thus, we could suggest that the crowdlending platforms have their own “optimal interest rate”, and are deliberately targeting a specific segment of the market.

The findings in 5.4 somewhat contradicts the previous argument, as we see that the corresponding bond rating equivalents are equally spread out, with a high proportion of AAA equivalent rated borrowers. This suggests that crowdlending platforms are targeting companies across all credit risk profiles.

6.2.2 Asymmetric information and adverse selection

Private investors often lack the competence to evaluate credit. Thus, they could face information assymetries when choosing which companies to lend to, and are dependent on platforms to take the same certification role as banks. Our regression results indicate that crowdlending platforms are realtively good at avoiding high risk borrowers. One can argue they perform their certification role.

At the same time, crowdlending platforms could themselve face asymmetric information issues. This is because they have less information than the borrowers’ regular bank. Controlling for this factor is difficult, since our dataset is based on publicly available information.

When looking at the distance between lender and borrower, described in section 4.1.1, we see that the platforms tend to accept more borrowers from their proximity. This could be a way for the platforms to adjust for asymmetric information, as underwriters would have a better understanding of the business’ surroundings.

Adverse selection theory would further suggest that crowdlending platforms would attract high risk borrowers, due to the high average interest rate on the platform. Even though crowdlending platforms seem to attract higher risk borrowers than banks, they are good at avoiding the worst cases. This suggests that they are aware of potential adverse selection issues and effeciently mitigate these.

6.3 Credit rating and interest rate analysis

From table 5.4.1, we see no clear pattern connecting a higher interest rate with a lower credit rating. This is not very intuitive at first sight, as one would not expect a company of high credit quality to accept an unreasonably high interest rate. We want to highlight two possible explanations: credit rationing and loan terms regulating collateral and covenants.

6.3.1 Loan terms

Interest reflects credit risk, which often is described as the product of probability of default and loss given default. The latter can be modified in a series of ways through increasing the collateral of a loan, or imposing covenants on the borrower.

One example could be a AAA rated company that wants to maximize its leverage. Say the bank is willing to lend up to 40% of a project's total value. If the company wants a 50/50 split between equity and debt, it could then borrow the remaining 10% of total project value through a crowdlending platform. The bank would then hold senior priority debt, while the crowdlending investors would hold junior priority debt, and thus expect to be compensated for this increased risk through a higher interest rate. In section 5.3, we show that crowdlending borrowers have a lower equity / total liabilities ratio. In other words they are already highly leveraged when approaching the crowdlending platform. A higher interest rate would therefore be acceptable, as the loan would hold junior priority, and thus have a higher LGD.

On the other end of the scale, triple C companies could face strict collateral terms, bringing down the expected LGD, and thus making a lower interest rate acceptable for investors. This dynamic could explain why the average interest rate remains approximately the same across all credit rating equivalents.

6.3.2 Credit rationing

Another explanation for the high interest rates could be credit rationing. If banks have an optimal interest rate, and are reluctant to lend at higher rates, this would generate a large underbanked segment. Given few options, the companies in this segment would be willing to accept higher interest rates at platforms, than what their risk profile would indicate. This is because leverage increase the return on equity, so long as the interest rate is below the return on capital.

Credit rationing could also mean that some high-quality borrowers that are indistinguishable from one another would not receive loans. These companies could also turn to crowdlending platforms, which represents an influx of capital for financing SMEs. As the high quality borrowers have no other options, they would also be willing to accept a higher interest rate, thus explaining why we find companies with AAA rating equivalents borrowing at 7%.

7. Robustness

In this section, we will briefly discuss issues that might affect our conclusions' robustness. We find it suitable to consider our data sample, the matching procedure and the models we deploy for the credit quality analysis.

7.1 Sensitivity analysis

To test the robustness of our findings, we perform a series of sensitivity analyses to see if they significantly change our findings.

7.1.1 Excluding Paris

In our data sample, a large share of the crowdlending borrowers are situated in Paris. This clustering could affect our findings. We therefore exclude Paris, and perform the same regression analysis as in section 5.1.5.

Table 7.1.1 Regression output when excluding Paris. Independent variable is the binary value "Crowdlend" where 1=Crowdlending borrower and 0=Regular borrower. Dependant variable is the score produced by each model.

	Altman Sabato	**Z''-score**	**Gloubos Grammatikos**	**Keasey McGuinnes**
crowdlend	-5.196**	-0.748	0.545	-0.736*
	(0.001)	(0.222)	(0.234)	(0.013)
_cons	57.25***	7.573***	2.613***	1.517***
	(0.000)	(0.000)	(0.000)	(0.000)
N	5248	5248	5248	5248

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From the regressions, we see that the same models still are significant. The Keasey McGuinnes model is relatively unchanged, while the Altman Sabato model coefficient has become even more negative for crowdlending borrowers. These results do not contradict any of our findings.

7.1.2 Increasing the cut-off points

In section 5.2, we analyze the cut-off points that tell us whether the companies are in high risk of default or not. We perform analyses up to cut-off point + 30%, as we find it likely that companies up to this point also would have a relatively high probability of financial distress. To see whether our results are robust, or simply mere luck, we increase the cut-off points by 50, 100 and 200%.

Table 7.1.2: Regression results against cut-off scores ranging from exact cut-off scores, to cut-off scores with increased (decreased) by up to 200%. * Denotes significance level where * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. (+) and (–) indicates the slope of the coefficient which is the binary variable "crowdlend", where 1 = crowdlending borrower and 0 = regular borrower. The dependent variable is a binary variable, where 1 = above cut-off and 0 = below cut-off. A positive slope coefficient will thus indicate a higher share of crowdlending borrowers above cut-off. Actual cutoff scores can be found in appendix 9.7.

Regression results

Distance from cut-off	**Keasey McGuinnes** [1]	**Gloubos Grammatikos**[2]	**Z" - score**[2]
—50%[1] & + 50%[2]	(–)***	(+)	(+)***
—100%[1] & + 100%[2]	(–)***	(+)	(+)***
—200%[2] & + 200%[1]	(+)	(+)	(–)

From the table above, we see that the findings remain the same until cut-off +/-100%. After that, the findings become inconclusive. This does not challenge the robustness of our findings.

7.2 Limitations

In this section, we will discuss the limitations of our findings. We will cover our selection of data sample, matching model, and credit scoring models.

7.2.1 Data sample

When generating our data sample, we have taken the utmost care trying to avoid sampling error, thus making an accurate sample. We have chosen a conservative approach, aware that there will always be risk of human error. Especially when generating a dataset from scratch and combining three different databases. Crowdlending platforms are reluctant to give out information about their borrowers, and do not produce comprehensive loan books. Thus, we find sampling the data ourself to be the best approach given available options.

Another shortcoming is the availability of panel data through our database. Amadeus has large gaps in their dataset, making it difficult to obtain a panel data sample with accounting information for companies over a series of consecutive years. Trying to collect three years of consecutive data per company reduced our post-cleaned sample from about 200 to below 30. If one can obtain panel data that spans three or more years, this would enable more accurate analyses.

Access to qualitative information about companies could increase the accuracy of our findings. Several studies have pointed out that qualitative information is important when evaluating the credit quality of SME borrowers, as discussed in section 4.1. Management experience, industry outlooks or the credit history of the owners and management, are examples of such qualitative data. Including this information in larger and more comprehensive credit models would probably increase model accuracy and reduce potential bias. This information is difficult to obtain through official databases such as Amadeus, which primarily contain accounting information. Thus, one is dependent on the goodwill of platforms to provide such information.

Furthermore, access to predicted loss given default for current loans, or historic data providing default rates and actual loss given default, would make the analyses more accurate. With access to this, it would be easier to evaluate whether the interest rates properly reflect the underlying risk, and therefore analyze the risk profile of the platform portfolios.

Crowdlending is a relatively new concept in continental Europe, and the data set is limited by the fact that the platforms began their operations late 2015. This means we only have access to accounting data up to the year 2016, and therefore limited ability to track the performance of each company in the years following the loan origination. Such data would provide insights into actual default rates and loss given default, making our analysis much more accurate. Looking at actual defaults is always better than using predictive credit scoring models, as predictions are never 100% accurate.

Our analysis is based on end of year accounts and P/L statements. This works well for ratios such as profitability and interest coverage. However, it does not necissarily represent a company's liquidity standing accurately. Cash may vary a lot from month to month, or even week to week. Data showing companies' liquidity through the year would thus allow for more accurate analyses.

7.2.2 Matching

There are many approaches for matching data. We found that the CEM procedure worked best for our purpose, as described in section 4.2. Still, all matching models are sensitive to what you choose as input variables. In our matching procedure, we are careful not to match based on the same variables being applied in our credit models. This is the reason why we have chosen large "bins" for the size variable. Smaller bins could probably yield more accurate matches, reducing imbalance further, but they could also affect our end results. Thus, choosing bin sizes equal to those used in the Amadeus database is a compromise between accuracy and inference. We find it a trade-off worth being aware of when interpreting our results.

One must also be aware that matching procedures merely mimick randomness, but do not guarantee a completely randomnized sample. This could affect our abilitiy to make causal inferences.

7.2.3 Credit scoring models

The credit scoring models are a vital part of our analysis into the credit quality of SMEs. It is also a common practice, with 70% of all US banks using credit scoring models in their small business lending (Mester, 1997). Although our selected credit models are widely used by banks and referenced in international literature, they are predictive and thus not 100%

accurate. This can easily be inferred from the fact that they produce different scores on our samples. We have tried mitigating this by deploying multiple models with different methodologies and that are based on samples from various countries and time periods. We have also looked for models that do well in model comparison studies. The models are predictive, and they should not be interpreted as conclusive. To get 100% accurate results, we must look at actual default statistics in the years following loan originations, instead of using predictive scoring models. A table showing the key features of our credit scoring models can be seen in section 3.1.

The models we use rely on either MDA or logistic methods for estimation. MDA-models have been criticized by Ohlson (1980). He points to the need for identical variance-covariance matrices, the difficulty of interpreting results, and multicollinearity. These issues could cause misleading model accuracy and unstable parameter estimates. Both the Z''-score (Altman E. , 1983) and the Gloubos Grammatikos (1984) models rely on MDA for model estimation. Despite the techniques' shortcomings, we chose the Z''-score model as it is the most widely used and internationally recognized credit scoring model. In the original 1984 paper, the Gloubos Grammatikos model was also estimated using logit, yielding quite similar results although a slighly different model with only three variables. The logit estimation technique is the preferred technique for estimating models, and the fact that the model was estimated both using MDA- and logit, strengthen our confidence in that the MDA-version of the model should work fine. The Altman Sabato model (2013) also relies on logit estimation technique.

Balcaen and Ooghe (2006) point out that there are several issues one must be aware of when estimating or using credit scoring models. One example is the problem of defining failure. While many models, including the ones we are using, are estimated using bankruptcy as dependent variable, credit events and defaults may occur long before that. Examples of such events can be creditors accepting haircuts, mergers and spin-offs. Other problems include non-stationarity, data instability and sampling selectivity due to oversampling of failing companies. All these issues must be taken into consideration when interpreting results from our credit scoring models.

Another disadvantage of credit scoring models is that they do not include qualitative data. Variables such as subjective judgments on intermediate and future financial situation, market position, management quality and relationship with credit institution have all been proven to greatly enhance the prediction power of credit scoring models (Lehman, 2003). This is because qualitative data is not measured through the financial databases we have access to, and therefore must be collected individually on a company-to-company basis.

Finally, our credit models are limited by the fact that they are not estimated on samples of French companies, but rather a mix of other companies from the UK, Greece and the US. This affect the models' accuracy and external validity to a French sample. We have tried to mitigate the effect by selecting models that have a proven track record across industries and borders, especially in Europe.

8. Conclusion

In this thesis, we have analysed the credit quality of companies borrowing from crowdlending platforms. We have applied four internationally recognized credit scoring models to a dataset of French companies, comparing crowdlending borrowers to regular bank borrowers.

Our findings show that crowdlending borrowers generally have a lower credit quality than regular borrowers. This could indicate that crowdlending platforms, being outsider lenders, face adverse selection problems. It could also indicate that the crowdlending platforms deliberately are not targeting the highest quality borrowers, making up for the increased risk with higher interest rates.

Our findings show that crowdlending platforms are quite good at avoiding the lowest quality borrowers. This could be an indication that crowdlending platforms are targeting companies within a specific risk band, avoiding both the highest and the lowest quality borrowers. It suggests that the platforms are good at shielding their investors from the potential asymmetric information issues they could face, by acting as intermediaries.

Finally, we find that although credit quality varies on the individual loans, the interest rate tends to remain around 7%. An explanation of this could be that platforms want a high interest rate to advertise to their investors, and therefore adjust loss given default through collateral requirements and covenants. It could also be a sign of credit rationing leading to companies of high credit quality unable to borrow from regular banks, and thus have no other option than to borrow at a higher price from crowdlending platforms.

8.1 Suggestions for further research

Crowdlending is a relatively new concept, and so far there has been few studies that explore these new capital markets. We believe more research should be done on the platforms' operations and risk pricing. With platforms maturing, following specific companies, looking at defaults, and thus getting more precise insights into the risk asessment done by the platforms will be easier. If proper data reflecting loss given default, such as covenants and collateral becomes available, studies could look more precicely into risk pricing done by the platforms.

On a macro level it could also be interesting to see the overall effects from crowdlending platforms on the SMEs opportunity to raise credit. Will the platforms compete with banks, or will they cater to a new segment in the market? Our findings indicate that the platforms will both compete with banks, while also servicing the lower ends of the market. As the markets grow in size, this dynamic could change.

Another interesting topic would be to look at the competitive dynamics between crowdlending platforms. One could say that platforms act as gatekeepers to their investor database. They evaluate risk and decide interest rate, and have the potential of engaging in relationship banking, thus generating similar dynamics as the regular banking market.

After the recession in 2008 the economy has had a slow recovery, however through quantitative easings and low interest rates we have experienced economic expansion in Europe the last few years, coinciding with the establishment of European crowdlending platforms. Litterature predicts that companies switching lender during times of economic expansion will perform worse and exhibit a higher likelihood of default. It could be interesting to investigate if this hypothesis holds for crowdlending borrowers, when data about actual defaults becomes available.

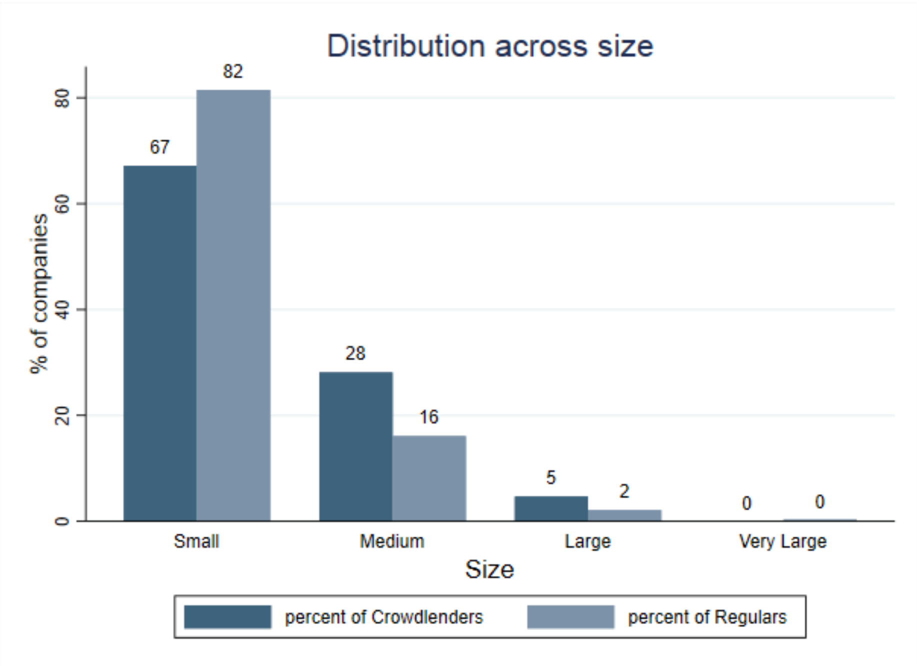
In section 5.1, we find several potential weak spots where the crowdlending borrowers show significantly lower scores than regular borrowers. As more data becomes available, it could be interesting to further investigate these differences. This would clarify whether they are the result of blind spots or a deliberate approach from the crowdlending platforms. An example of this could be to look into the weaker scores of the administration and science sector. This could be a weak spot where the crowdlending platforms are not as good as banks. It could also be a consequence of crowdlending platforms valuing immaterial assets such as patents higher than banks.

9. Appendix

9.1 Crowdlending borrowers with debt to financial institutions

Type of debt	**Number of companies**
Short term	91
Long term	89
Short- & long term	75
No debt	0

9.2 Distribution of companies across size



9.3 Regression output for all credit ratios

Below follows regression outputs for all 14 credit ratios used in the credit models. The independent variable is the binary value “Crowdlend”, where 1 = Crowdlend and 0 = Regular. The dependant variable is the credit ratio.

	EBIDTA/Total Assets	**Working Capital/Total Assets**	**Equity/Total Liabilites**	**EBITDA/Interest expenses**	**Creditors Turnover**
crowdlend	0.00180	0.0567	-0.576***	-933.9	-2.683**
	(0.927)	(0.253)	(0.000)	(0.095)	(0.005)
_cons	0.120***	0.148***	1.186***	970.3	5.978***
	(0.000)	(0.000)	(0.000)	(0.082)	(0.000)
N	5492	5492	5492	5492	5492

	Retained Earnings/Total Assets	**EBIT/Total Assets**	**Curr. Liabilities/Equity**	**Cash/Total Assets**	**Current Ratio**
crowdlend	-0.134**	-0.00162	-1.052	-0.0988***	-0.280***
	(0.003)	(0.929)	(0.320)	(0.000)	(0.000)
_cons	0.361***	0.0853***	3.811***	0.173***	1.613***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	5492	5492	5492	5492	5492

	Non curr. liabilities/Total Assets	**PL before tax/Sales**	**PL before tax/Total Assets**	**EBITDA/Curr. Liabilities**
crowdlend	0.0219	0.00353	-0.00641	-0.0801
	(0.484)	(0.753)	(0.728)	(0.341)
_cons	0.114***	0.0475***	0.0799***	0.364***
	(0.000)	(0.000)	(0.000)	(0.000)
N	5492	5492	5492	5492

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

9.4 Credit ratios featured in the credit scoring models

Category	Ratio	Z''-score	Altman-Sabato	Gloubos-Grammatikos	Keasey-McGuinnes
Leverage	$\frac{Equity}{Total\ Liabilities}$	Yes	Yes		Yes
	$\frac{Short\ Term\ Debt}{Equity}$		Yes		
	$\frac{Long\ Term\ Liabilities}{Total\ Assets}$			Yes	
	$\frac{Current\ Assets}{Current\ Liabilities}$			Yes	
Coverage	$\frac{EBITDA}{Interest\ Expenses}$		Yes		
	$\frac{EBITDA}{Short\ Term\ Liabilities}$			Yes	

Category	**Ratio**	**Z''-score**	**Altman-Sabato**	**Gloubos-Grammatikos**	**Keasey-McGuinnes**
Liquidity	$\frac{Working\ Capital}{Total\ Assets}$	Yes		Yes	
	$\frac{Cash}{Total\ Assets}$	Yes	Yes		
	$\frac{Purchases}{Accounts\ Payable}$				Yes
Profitability	$\frac{Retained\ Earnings}{Total\ Assets}$	Yes	Yes		
	$\frac{EBIT}{Total\ Assets}$	Yes			
	$\frac{EBITDA}{Total\ Assets}$	Yes	Yes		
	$\frac{\frac{P}{L}\ before\ taxes}{Sales}$				Yes
	$\frac{\frac{P}{L}\ before\ taxes}{Total\ Assets}$			Yes	

9.5 Summary table of variables

BvDEP ID Number	Unique company ID in Amadeus database
Country	Country of company location
Reporting basis	Reporting standard of company
Close date	Date of accounts
Close date year	Year of accounts
Accounting practice	Reporting preactice for accounting
Current assets	Total current assets & prepaid exp.: net figure +
Cash	Marketable securities: net figure + Cash and banks:
Total Assets	Total assets: net figure + Deferred charges + Bond redemption premiums + Assets conversion adjustments Cap. Subscribed, called, unpaid: net figure
Shareholder funds	Total shareholders funds + Total other equity Uncalled share capital Cap. Suscribed, called, unpaid: net figure
Other Shareholder funds	Retained earning ("Reserve comptable" and "report á nouveau")
Non Current Liabilities	Total prov. for liab. and ch. + Total debts: Due between 2 & 5 years + Total debts: Due beyond 5years
Non Current Liabilities, Long term debt	Convertible bonds + bank borrowings repayable + bank borrowings + other borrowings (due 2 - 5 years)
Current liabilities	Total debt and anticipated rev. + Liab. Conversion adjustments Total debts (due between 2 - 5 years) - Total debts (due beyond 5 years)
Current liabilities: loans	Convertible bonds : Due within one year + Other bonds : Due within one year + bank borrowings
Current liabilities: creditors	Creditors
Working capital	Raw materials and consumables + Work in progress + Services in progress + semi-finished and finished + goods for sale + trade debtors - creditors
Operating revenue (Turnover)	Total Operating Revenue

9.6 T-tests for credit scores across key covariates

The following tables show the results from t-tests run on the difference in credit scores between regular and crowdlending borrowers on key covariates.

Table 9.6.1: T-tests for credit scores across size

	Z-score			**Altman Sabato**		
Size	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**
Average values						
Regular	8,4	8,2	7,1	54,3	56,9	56,5
Crowdlend	6,9	6,1	6,7	50,4	50,4	53,1
Two sided t-test						
T statistic	1,28	4,34	1,40	0,94	4,64	4,34
P value	0,200	0,000	0,163	0,349	0,000	0,000

	Gloubos Gramatikos			**Keasey McGuinnes**		
Size	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**
Average values						
Regular	2,5	2,2	2,7	0,8	1,2	1,5
Crowdlend	1,9	2,8	3,2	0,2	0,6	0,9
Two sided t-test						
T statistic	0,46	-1,44	-2,18	1,00	2,92	3,78
P value	0,642	0,149	0,029	0,316	0,004	0,000

Table 9.6.2: T-tests for credit scores across industry

Z-score	**Adm.**	**Construct.**	**Educ.**	**Entertain.**	**Info.**	**Manufact.**	**Retail**	**Science**	**Transport**
Average values									
Regular	7,9	8,2	8,7	6,2	6,1	7,9	7,5	7,7	5,7
Crowdlend	5,4	6,9	5,9	6,0	5,2	6,9	6,7	8,3	5,5
Two sided T-test									
T statistic	2,95	2,04	-	0,13	0,64	1,53	1,73	-0,72	0,30
P value	0,003	0,041	-	0,894	0,520	0,125	0,083	0,473	0,766

Altman Sabato	**Adm.**	**Construct.**	**Educ.**	**Entertain.**	**Info.**	**Manufact.**	**Retail**	**Science**	**Transport**
Average values									
Regular	58,2	57,9	56,7	53,1	54,7	57,6	55,9	57,8	56,4
Crowdlend	50,9	52,3	49,9	53,0	51,5	51,6	52,7	53,6	52,1
Two sided T-test									
T statistic	2,82	2,72	-	0,00	0,63	3,35	2,90	2,08	2,65
P value	0,005	0,007	-	0,998	0,527	0,001	0,004	0,038	0,008

Gloubos Grammatikos	**Adm.**	**Construct.**	**Educ.**	**Entertain.**	**Info.**	**Manufact.**	**Retail**	**Science**	**Transport**
Average values									
Regular	2,5	2,6	2,6	1,6	2,4	2,7	2,5	2,6	3,1
Crowdlend	2,6	2,9	4,1	3,1	2,9	2,9	2,7	3,5	3,9
Two sided T-test									
T statistic	-0,14	-0,56	-	-0,70	-0,33	-0,41	-0,71	-1,59	-1,65
P value	0,891	0,574	-	0,481	0,744	0,681	0,477	0,111	0,099

Keasey McGuinnes	**Adm.**	**Construct.**	**Educ.**	**Entertain.**	**Info.**	**Manufact.**	**Retail**	**Science**	**Transport**
Average values									
Regular	0,4	1,0	0,0	0,4	0,2	0,8	1,7	0,5	1,6
Crowdlend	0,2	0,5	-0,1	0,0	0,2	0,6	1,4	0,2	0,9
Two sided T-test									
T statistic	0,7	2,1	-	1,3	-0,2	1,0	1,3	1,1	2,1
P value	0,485	0,038	-	0,184	0,875	0,312	0,181	0,263	0,039

Table 9.6.3: T-tests for credit scores across age

	Z-score				Altman Sabato			
Age	**0-2**	**2-5**	**5-8**	**8+**	**0-2**	**2-5**	**5-8**	**8+**
Average values								
Regular	4,7	5,0	5,5	7,4	52,7	53,8	55,2	56,7
Crowdlend	5,5	5,7	6,4	6,7	50,5	52,6	52,4	52,3
Two sided t-test								
T statistic	-1,04	-1,02	-1,48	2,21	0,79	0,70	1,91	5,68
P value	0,300	0,306	0,139	0,027	0,430	0,485	0,056	0,000

	Gloubos Gramatikos				Keasey McGuinnes			
Age	**0-2**	**2-5**	**5-8**	**8+**	**0-2**	**2-5**	**5-8**	**8+**
Average values								
Regular	2,0	3,0	3,3	2,6	1,6	1,6	1,6	1,5
Crowdlend	1,8	3,0	3,2	3,1	0,3	0,7	0,7	0,9
Two sided t-test								
T statistic	0,24	0,02	0,40	-2,12	2,19	2,42	2,61	4,05
P value	0,812	0,987	0,689	0,034	0,028	0,015	0,009	0,000

Table 9.6.4: T-tests for credit scores across region

Region	Z-score North east	North west	South east	South west	Altman Sabato North east	North west	South east	South west
Average values								
Regular	7,8	7,5	6,6	6,3	56,6	56,8	54,5	56,2
Crowdlend	6,8	6,5	5,7	6,5	52,2	50,3	57,0	53,8
Two sided t-test								
T statistic	1,74	2,56	0,77	-0,28	3,11	5,93	-0,75	2,41
P value	0,081	0,011	0,441	0,780	0,002	0,000	0,455	0,016

Region	Gloubos Grammatikos North east	North west	South east	South west	Keasey McGuinnes North east	North west	South east	South west
Average values								
Regular	2,5	2,7	2,7	2,9	1,4	1,4	1,9	1,5
Crowdlend	3,2	3,4	2,8	2,7	1,0	0,8	1,0	0,7
Two sided t-test								
T statistic	-1,69	-2,35	-0,03	0,61	1,87	2,99	1,29	4,00
P value	0,091	0,019	0,980	0,543	0,062	0,003	0,198	0,000

9.7 Regression output on cut-off scores

Below follows a series of regression output tables that were used to produce the tables in section 5.2 and 7.1.2 Independent variable is the binary value "Crowdlend" 1=Crowdlend and 0=Regular The dependent variable is a binary variable, where 1 = above cut-off and 0 = below cut-off. A positive slope coefficient will thus indicate a higher share of crowdlending borrowers above cut-off.

Table 9.7.1 Regression against exact cut-off scores..

	Keasey McGuinnes	**Gloubos Gramatikos**	**Z-score**
crowdlend	-0.391***	0.0558	0.0110
	(0.000)	(0.424)	(0.262)
_cons	0.696***	0.868***	0.979***
	(0.000)	(0.000)	(0.000)
N	5492	5492	5492

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9.7.2 Regression against cut-off scores, +/- 10%.

	Keasey McGuinnes	**Gloubos Grammatikos**	**Z''-score**
crowdlend	-0.379***	0.0638	0.00273**
	(0.000)	(0.386)	(0.001)
_cons	0.732***	0.851***	0.997***
	(0.000)	(0.000)	(0.000)
N	5492	5492	5492

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9.7.3 Regression against cut-off scores, +/- 20%.

	Keasey McGuinnes	**Gloubos Grammatikos**	**Z''-score**
crowdlend	-0.395***	0.0731**	0.00327***
	(0.000)	(0.009)	(0.000)
_cons	0.776***	0.841***	0.997***
	(0.000)	(0.000)	(0.000)
N	5492	5492	5492

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9.7.4 Regression against cut-off scores, +/- 30%.

	Keasey McGuinnes	**Gloubos Grammatikos**	**Z''-score**
crowdlend	-0.343***	0.0729	0.00428***
	(0.000)	(0.345)	(0.000)
_cons	0.809***	0.832***	0.996***
	(0.000)	(0.000)	(0.000)
N	5492	5492	5492

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9.7.5 Cut-off + 50% (-50% for Keasey McGuinnes).

	Keasey McGuinnes	**Gloubos Grammatikos**	**Z''-score**
crowdlend	-0.0854***	0.0215	0.00162***
	(0.000)	(0.348)	(0.000)
_cons	0.887***	0.811***	0.994***
	(0.000)	(0.000)	(0.000)
N	5492	5492	5492

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9.7.6 Cut-off + 100% (-100% for Keasey McGuinnes).

	Keasey McGuinnes	**Gloubos Grammatikos**	**Z''-score**
crowdlend	-0.0476^{***}	0.00900	0.00305^{***}
	(0.000)	(0.727)	(0.000)
_cons	0.986^{***}	0.738^{***}	0.989^{***}
	(0.000)	(0.000)	(0.000)
N	5492	5492	5492

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9.7.7 Cut-off + 200% (-200% for Keasey McGuinnes).

	Keasey McGuinnes	**Gloubos Grammatikos**	**Z''-score**
crowdlend	0.0000189	0.0210	-0.00159
	(0.318)	(0.472)	(0.897)
_cons	1.000^{***}	0.524^{***}	0.954^{***}
	(0.000)	(0.000)	(0.000)
N	5492	5492	5492

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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