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Institutions and retail investors in the Peer-to-peer lending market

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Abstract

P2P lending is a market that has emerged from the FinTech industry, which aims to provide funding to those who cannot get funding from traditional banks. The market was intended for retail investors, but as the market has matured, larger financial institutions have begun to take an increasing part in the market. It is speculated that investors will outperform retail investors due to their capital powers and investment strategies, as they compete in the same market for a fixed amount of assets. This paper aims to deepen our understanding and find supportive documentation for these speculations. We have defined our research question:

"Will institutionalization of the P2P lending market have a negative effect on the retail investor?"

To answer this question, we have primarily used a quantitative approach with supportive secondary research papers to confirm our findings. The quantitative approach included several regression models and an evaluation of descriptive statistics from the dataset retrieved from Prosper Marketplace. Our results were supportive of our research question and prove that institutional investors outperform retail investors in the market of P2P lending.

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1 Introduction

Peer-to-peer (P2P) lending was initially offered as a solution for consumers to seek personal loans from newly developed lending platforms such as the British company ZOPA, which began its operations in 2005. The loans that ZOPA provided were funded by retail investors (Ziegler & Shneor, 2020). By 2010, other P2P lending models were developed to focus on providing finances for Small and Medium-sized (hereafter 'SME') companies that struggled to get financing from traditional banks. In addition, SME companies found that they could potentially benefit from lower interest rates by borrowing from retail investors (Cortese, 2014).

As the crowdfunding market increasingly matures and regulations start to allow it, institutions seem to find their way into these markets. This is a somewhat controversial movement as the concept of crowdlending aims to avoid financial institutions, but now these institutions have involved themselves in the lending market (Wei, 2015). At this point, institutional investors make up the majority of P2P lenders. Researchers such as Wei (2015) propose that over two-thirds of lenders are institutions, and other researchers propose that institutions account for more than 80 percent (Cortese, 2014). According to The Global Alternative Finance Market Benchmarking Report (2020) conducted by the University of Cambridge, Italy is the most institutionalized country in Europe, as 93 percent of capital in crowdfunding is institutional capital.

1.1 Background and motivation

In our Master Thesis, we intend to investigate the market of P2P lending in Crowdfunding. P2P lending was initially a market for individuals and SMB-companies to seek financing from retail investors because of their unavailability of getting funding from banks. However, in recent years, there has been an increasing inflow of institutional investors that invests in these loans. We aim to understand better the underlying reason for this and what impact this could have on the retail investors. The interesting part is that this was supposed to be a market without the participation of financial institutions. Still, they seem to have found their way into

the market. There are many speculations that the inflow of institutions in the P2P lending market will hurt retail investors because of the institutions' enhanced ability for investment analysis and capital power. Financial institutions often use algorithmic trading as an investment strategy, implying that institutions could “cherry-pick” the best investment opportunities (loans), leaving the worst for the retail investors. We are going to investigate whether or not this might be the case.
The financial industry's fundamental function has always been to choose which businesses and individuals receive loans and investments to help them develop and succeed (Magnuson, 2018). Banks have long dominated this procedure. However, the global expansion of crowdfunding has disrupted banks' monopolies on both loan and equity financing. Regarding fundraising for individual and professional actors, this new industry provides alternative finance, which challenges the existing financing industry. Furthermore, the FinTech industry has changed the traditional banking and equity financing for startups in general (Baeck 2014).

The motivational factor regarding this topic is to deepen our understanding of a constantly developing and rapidly growing market in FinTech. It is fascinating to investigate a market meant for one type of investor being infiltrated by another and what impact that will have on the market. It is also inspiring to perform a study in a relatively new field without much previous research. We believe this paper will be an excellent contribution to the topic, and we have defined our research question: “Will institutionalization of the P2P lending market will have a negative effect on the retail investor?”,

1.2 Summary

Our paper is based on quantitative and secondary research data. Secondary research data is mainly used to confirm or disprove our results from our quantitative research, which is our primary method. We have used high-quality cited papers on sites such as Google Scholar as our secondary research data. Our primary quantitative data is a dataset from Prosper Marketplace, an American crowdfunding platform. The original uncleaned dataset that we have used contains data from 113 938 loans with 81 variables each. The dataset was then cleaned to extract only those variables relevant for our research.

The dataset we used had no variable for whether the loan was bought (invested in) by a retail investor or an institutional investor. As a crucial part of this paper's purpose includes comparing retail investors and institutions, we had to sort institutions and retail investors in the dataset by making a dummy variable. This dummy variable was determined by three assumptions about the number of investors invested in a loan, the total amount of the loan, and the average funding amount for investors. By doing so, we could make two subsets of the dataset where we sort the dummy variable that equals 1 (institutional investors) and the dummy variable that equals 0 (retail investors).

To find what affect institutional investors have on retail investors in the P2P lending segment, we compared the descriptive statistics for the two datasets and ran several regressions. For the descriptive statistics, we found that institutional investors outperform retail investors in the yield received by 60 basis points. Interestingly, the higher yield awarded to institutions also comes with a lower standard deviation by 140 basis points. However, the estimated loss is 80 basis points higher for institutions but with a standard deviation of 70 basis points lower than retail investors. We also found institutions to have a lower default rate than the retail investors and a significantly higher Sharpe ratio. We calculated the expected loss for both populations by combining the estimated loss and the default rate to find that the expected loss for retail investors is significantly larger than for institutions.

For the two newly developed datasets, we ran a linear regression for both "lender yield" and "estimated loss" (dependent variable) to test whether or not they are affected by the number of investors in each loan, total loan amount, and the average funding amount (independent variables). We found that institutional investors are indifferent about how much capital they invest regarding yield, in contrast to retail investors that gain less yield the more they invest. Regarding estimated losses, institutions also receive a lower estimated loss for higher amounts invested, while retail investors receive a higher estimated loss for a higher amount invested. This is considered a huge advantage for institutions, especially since it can be assumed that financial institutions often have way more capital power for investments.

Institutions get a higher lender yield with a lower standard deviation, leading to a significantly higher risk-adjusted return. Institutions have access to more capital, and we find that institutions are indifferent in what loan amount they invest, whereas retail investors seek out the lower amounted loans. On another note, we find that retail investors, on average, have a lower estimated loss on the loans they invest in. Our findings reveal that more loans invested by retail investors default than those invested by institutions. Combining this with the estimated loss, we find that retail investors have a much worse expected loss. With evidence suggesting higher estimated loss gives higher lender yield, institutions can invest in loans with higher lender yield and lower risk. One could also argue that institutions are more diversified than retail investors, reducing the risk even further. Institutionalization has great potential to affect the regular retail investor in the crowdlending market, although the effect is driven by institutions outperforming retail investors.

1.3 Crowdfunding

Crowdfunding is an open invitation to contribute financial recourses to a retail or institutional investor. This process is most commonly done through internet-based crowdfunding platforms (Belleflame, Omrani, & Peitz, 2015). The crowdfunding platforms arrange loans by bringing together lenders and borrowers. Crowdfunding allows retail investors and small businesses to lend to one another over the internet, bypassing the banks and financial institutions in the process (Wei S., 2015). The most popular crowdfunding mechanisms are auctions and posted prices. The "crowd" determines the price through an auction process in auctions. When the crowdfunding platform sets a price, it is called a posted price (Wei & Lin, 2015).

While the phrase "crowdfunding" refers to a request for funds from a large number of people via an internet platform, there are four types of crowdfunding methods. Belleflame & Lambert (2014) identify these as donation-based, reward-based, lending-based, and equity-based models. In donation-based models, the donors donate funds where they do not expect any material rewards in return for their contribution (Giudici, Riccardo, Lamastra, & Verecondo, 2012). Reward-based crowdfunding is based on a smaller monetary reward for contributing. This contribution could be pre-paying for a product. Donation- and reward-based crowdfunding can be referred to as "community crowdfunding" (Kirby & Worner, 2014). Crowdfunding platforms providing the lending model offer interests on investment contracts, generally a fixed interest rate. Within this model, one invests with an expectation of profits (Bradford, 2012). Similar to the lending-based model, equity crowdfunding can be defined as “Financial Return Crowdfunding” (Kirby & Worner, 2014). Contributors to this type of crowdfunding will receive a share in the profits of the business they invest in (Belleflamme & Lambert, 2014). A stake in the company is typically used to partake in the profits. Due to the extensive due diligence process associated with this investment, equity crowdfunding is considerably more complicated than the other forms of crowdfunding (Vulkan, Åstebro, & Sierra, 2016).

Crowdfunding platforms provide the opportunity to develop a new, engaging, and dynamic mechanism for allocating capital from traditional, institutional stakeholders, such as banks, to individual-driven operations that use existing and future technology to reach millions of people looking for investment possibilities (Colgren, 2014).

The public authorities greatly influence how the crowdfunding industry develops. By setting regulations, the authorities decide the rules each crowdfunding model practices under to protect the consumer and investor (Shneor, Zhao, & Flåten, 2020). The crowdfunding market relies on suitable regulated structures. Regulation is one device that organizations need to deploy in their efforts to gain trust (Nienaber, Hofeditz, & Searle, 2014).

1.4 Peer-to-peer lending

When studying crowdfunding, it is crucial to contemplate which type of crowdfunding is being studied (Ahlers, Cumming, Günther, & Schweizer, 2012). Going forward, our primary focus will be debt-based, specifically peer-to-peer lending.

Debt-based crowdfunding has experienced an evolution from more personalized loans into more sophisticated and specialized products. These products consist of lending arrangements such as crowdfunded business loans, student loans, asset-based loans, and bitcoin-based loans (Everett, 2019). This type of loan involves three parties: Investor, intermediate, and borrower. The intermediate who facilitates these loans are the crowdfunding platforms (Valanciene & Jegeleviciute, 2013).

Institutionalization refers to the proportion of volume attributed to institutional investors, such as pension funds, mutual funds, asset management firms, and banks, in what is otherwise labeled as 'the crowd' (Ziegler & Shneor, 2020). Nasdaq defines institutionalization as: "The gradual domination of financial markets by institutional investors, as opposed to individual investors. This process has occurred throughout the institutionalized world" (Nasdaq, n.d.). The definition presented by Nasdaq perfectly reflects our understanding of the term in this paper.

2 Literature review

Our paper builds on previous research papers which aim to evaluate institutions' profitability in a crowdfunding market and how institutions may outperform retail investors and seek out their advantages, such as algorithmic investment strategies. Our paper builds on these findings and aims to research the following risk for both institutions and retail investors to evaluate the risk-adjusted return better and further evaluate whether the institutional inflow in the market impacts retail investors. Our research will contribute to making a better overall understanding of the matter.

As discussed earlier, institutions picking loans through algorithmic trading could be a huge advantage. If institutions were to invest in the best loans on the market, retail investors are likely stuck with the worst. Retail investors often cannot analyze and evaluate risks and make investment decisions at the same rate as institutions using algorithms (Wang & Overby, 2020). As an increasing number of institutions enter the market with algorithms, we consider this a disadvantage for retail investors.

On the other hand, Wang & Overby (2020) argue that the increasing participation by institutional investors leads to an overall market growth that could benefit retail investors. It is argued that algorithmic trading will decrease funding time and increase decision efficiency, attracting more borrowers to the lending platforms (Wang & Overby, 2020). The logic behind this argument is that the increased market size will allow retail investors to still invest in high-quality loans without being run over by institutions. Wang & Overby (2020) primarily investigated the effect of algorithmic trading in regards to interest rate, which differs from our paper as we compare the risk-adjusted return between the two groups.

Matt Burton, the CEO of Orchard, a company that helps institutions invest in P2P loans, states: “To eke out better returns, many fund managers then use their own credit algorithms to identify loans that may be underpriced or overpriced, and cherry-pick the ones they want.” (Cortese, 2014). The founder of Lend Academy, Peter Renton, says: “The fastest computer right now is getting the most loans.” In addition, it is stated that some hedge funds have installed services close to Lending Club and Prosper Marketplace to get an advantage (Cortese, 2014). However, both Lending Club and Prosper have upper limits on how many percentages of the loans institutions can acquire. Mr. Laplanche, the founder of Lending Club, told The New York Times: “We want to be extremely careful and not let a handful of investors drive our expansion” (Cortese, 2014).

Mohammadi & Shafi (2017) performed a study highlighting how large advantage institutions have compared to retail investors. The study has two significant findings. Firstly, they documented that the “crowd,” retail investors, on average underperform institutional investors. Retail investors earned on average 40 basis points less in interest rates than institutions without a significant decrease in risk.

One of the drivers behind the differences is highlighted by an analysis of “recycled loans,” where loans left unfunded by institutional investors often became funded by retail investors. The institutional investors rejected these loans based on criteria that were not visible to the average retail investor. On the other hand, institutions have access to econometricians who can observe these criteria more easily. The recycled loans alone contribute to 20 basis points less in interest return for the retail investor. Mohammadi & Shafi (2017) further argue that these findings might indicate that some of the conditions in the crowdfunding market necessary to produce wisdom for the crowd are violated, giving an advantage to institutional investors (Mohammadi & Shafi, 2017). This paper is useful for our research, as we can compare the difference in interest rate to our findings, which are found by a different approach.

3 Theory

This section will discuss why we believe that "institutionalization of the P2P lending market will have a negative effect on the retail investor." This is also our main hypothesis. We will highlight the three main advantages we believe institutions have over retail investors, which we used to develop our hypothesis and research question. The main advantages are their possible algorithmic investment strategies, information asymmetry, and crowdlending-platforms signaling to exit the retail market.

3.1 Algorithmic investment strategies

As the P2P lending market has evolved and matured and the institutions established themselves in crowdfunding, the uprise of algorithmic risk assessment and loan picking came along. Several institutions aim to redefine how loans get evaluated as investment opportunities by implementing algorithms that can make quick investment decisions (Morgan Stanley, 2015). It is hard to know which data points these algorithms use to pick loans as algorithms are generally proprietary, and it would most likely vary between institutions (Ziegler & Shneor, 2020). However, these algorithms likely find their investment objectives based on their prediction of a borrower's creditworthiness based on big data and machine learning (Havrylchyk, 2018). The interesting part is the effect of these algorithms in a smaller market, such as the market of P2P lending, where algorithms and retail investors compete for the same fixed sets of assets.

Institutions can make faster-acting and better-informed investment decisions by implementing algorithms in their strategy than retail investors are able to. Algorithms act much faster as their decision-making is based on their input of data points discussed above. Also, algorithms contain information based on statistical models based on big data sets, which results in better-informed decision-making (Wang & Overby, 2020). Based on this premise, one can argue that algorithmic trading will give institutional investors an advantage over retail investors. Consequently, it negatively affects retail investors, where institutions can invest in high-performance loans more quickly.

3.2 Information asymmetry in Crowdlending

Investors on crowdfunding platforms face uncertainties about supplier characteristics and the risk of quality cheating. This difference in knowledge between the investor and the borrower is defined as information asymmetry (Mishra, Heide, & Cort, 1998). "Similar to other two-sided markets, decision-making processes on crowdfunding platforms are characterized by asymmetric information between the two market sides" (Wessel, 2016, p. 16).

Lenders in peer-to-peer lending have to make decisions based solely on information published by the borrowers without being sure about its authenticity (Ribeiro-Navarrete, Piñeiro-Chousa, López-Cabarcos, & Palacios-Marqués, 2021). These negative implications caused by information asymmetry have led to crowdfunding platforms using rating-based models to evaluate and rank the loans (Bastani, Asgari, & Namavari, 2019). The crowdfunding platform tries to give as much information on the borrowers as possible, such that the lenders get more knowledge about the characteristics of the borrowers (Serrano-Cinca & Gutiérrez-Nieto, 2016).

Based on the characteristics of the fundraiser and the performance of all successful campaigns, the lending-based platforms assigns a credit rating to each campaign. As a result, it can be considered a credit-rating agency for borrowers (Belleflame, Omrani, & Peitz, 2015). Crowdfunding platforms use machine learning algorithms to assign an accurate credit rating. These algorithms offer high prediction performance, but most lack explanatory power (Ariza-Garzón, Arroyo, Caparrini, & Segovia-Vargas, 2020).

Loans with higher risk will include a higher interest rate. In this way, the investor will get more rewarded the more risk-seeking they are. However, the information asymmetry between the lender and borrower is a problem where the lender is unaware of the borrower's reliability (Bastani, Agari, & Namavari, 2019). This is not a flawless system, and it would be beneficial to be able to identify loans posted with a deviant interest rate. If institutions can better identify these types of loans, one could argue it would result in an advantage for institutional investors.

Wessel (2016) identifies two main issues regarding information asymmetry in crowdfunding. Crowdfunding campaigns are generally a one-off process for the project creator. As a result, the quality of the project one invests in will solely be evaluated after the campaign has ended. In comparison to platforms like eBay and Airbnb, one can read user reviews before making a decision. These reviews are part of a reputation system that enhances transparency and give information on the participant's historical performance (Luca, 2017). Second, project creators can use the information asymmetry by overstating the quality of their projects and withholding information. This way, the borrower can portray their low-quality project as high-quality (Agrawal, Catalini, & Goldfarb, 2014). There is an incentive for the borrower to hide some key characteristics to obtain a lower interest rate on their loan (Backman et al., 2011). These issues result from information asymmetry and lack of available project information. Because of this, funders lack the necessary information to estimate the chance that a project will succeed (Wessel, 2016).

3.3 Platforms exiting the retail market

In addition to LendingClub, smaller platforms such as ThinCats, Landbay, and Zopa closed their business for retail investors to favor their institutional relationships (Shoffman, 2020). When a leading market participant makes a huge decision like this, it could communicate to the rest of the market that the original P2P lending model where retail investors are in focus is a dying strategy and that focusing on institutional investors is more beneficial. This is a problem for retail investors.

Even though there are some indications made by market participants that institutions are the way to go, there is no guarantee that others will follow. At least not by entirely excluding retail investors. Peter Renton (2020), the founder of Lend Academy, reached out to Prosper Marketplace to get an insight into their future plans in regards to retail investors, and the response he got was: “that they are still open for investment and remain 100% committed to retail investors” (Renton, 2020). Consequently, if platforms were to exit the retail market, the P2P lending market would be significantly reduced for retail investors to participate, increasing the competition.

4 Methodology

In this section, we present the methodological choices to answer our research problem. Kvale & Brinkmann (2009) define methodology as a "systematic procedure for observation and analysis of data." In the first part, we show the background of our methodological choices. In addition, we opted to present the various methods we utilized, along with a brief description of each.

4.1 Research approach

In this thesis, we have used quantitative and secondary research and data to support our findings. "Secondary data analysis is an analysis of data collected by someone else for another primary purpose" (Johnston, 2017). As students with limited time and resources, we use secondary data to back up or disprove our primary findings as a viable option.

Crowdfunding platforms operate online, allowing us access to published data. As there are available quality data from a credible crowdlending platform, our primary focus remains on the quantitative approach. Using this quantitative approach, we will gather data from a population, which we use as a representative for the entire crowdfunding market. We aim to perform a quantitative analysis of this data set to disprove or prove our research question. "If you are carrying out research into people's opinions, feelings, experiences or behavior, you will be following one of two distinct paths" (Davies & Hughes, 2014). Therefore, we will conduct our quantitative analysis before looking at secondary analysis to complement our findings. In this way, we will not have predefined conceptions of which way our results should go.

4.2 Data and data sources

Our research question only deals with the investors in lending-based crowdfunding. We collected data from a lending-based crowdfunding platform to obtain the most representative dataset. This way, we would not get skewed results from the other types of crowdfunding. The platform we used for our dataset is called Prosper.

Prosper is the first peer-to-peer lending platform in the United States, with more than $19 billion in loans and more than 1.140.000 borrowers. Prosper focuses on personal loans similar to those offered by banks (Cumming & Sewaid, 2021). Prosper's lending process started as an auction mechanism where the investors could bid on the loans they were interested in funding, with a proposed amount and interest rate. Later, Prosper changed to a posted-price mechanism where they offered a preset rate on the loans.

Since 2011, Prosper has worked in the following way:

(1) The borrower submits a loan request to Prosper.com, where they provide the necessary financial information

(2) Prosper.com review the loan request and analyzes the financial information to set an appropriate interest, and publishes the loan request

(3) Investors select which listings they want to fund, and with what amount.

(4) Depending on the borrowers' choice, they will receive the requested amount if they attract sufficient investment of either 70% or 100% of the principal.

One needs to create a Prosper account to extract loan data from Prosper. However, this is only available for United States citizens. To bypass this problem, we used a pre-existing dataset created and used in several other research papers. The data on these loans are publicly offered information. Because of this, we believe it is valid to use a pre-existing dataset. This dataset has been used in several other cited papers and is available on data and code-sharing sites such as github.com and Kaggle.com.

In this exploratory data analysis, we first had to clean the Prosper dataset containing loan information for over 100.000 loans between 2006 and 2013. We could observe 81 different variables for each individual loan, giving information on the borrower and the loan characteristics. As we had an idea of what variables could be most interesting to our research, we created a subset of the data, where we eliminated the variables that had no use.

4.2.1 Defining institutional investors

We depend on sorting out institutions and retail investors to explore our research question with this dataset. Originally this was not divided in the dataset, and there

was no way of knowing if the investors in each loan were institutions or retail investors. We created two subsets of the cleaned data version to solve this problem. To sort this most accurately, we used the variables “investors” and “loan original amount.” The variable “investors” describes how many investors that invest in the loans. The “loan original amount” gives information on how large the loan is in American dollars. By assumption, retail investors invest much smaller amounts than institutional investors because of their higher capital power. Consequently, we assume that loans with a high loan original amount and a low number of investors are loans with institutional investors. In contrast, loans with a lower loan amount and a higher number of investors are retail investors. To better fit our sorting process, we have included one variable which defines the average funding amount per investor. We have also excluded the population's mid-portion to avoid loans that appear uncertain regarding the sorting process. We have excluded loans that contain investors between the 9-115 investors (30th-75th percentile) as they are more challenging to evaluate whether they are retail or institutional investors.
Our parameters are set by dividing the three variables into percentiles presented in table 1. Firstly, the number of “investors” is predicted to be in the lower end when we determine institutional investors.

We predict that the number of investors could be more than 2 (25th percentile) but should never be as high as 44 (50th percentile). Therefore, we believe that setting our parameter to less or equal to 9 investors (30th percentile) would be a good fit when determining institutional investors. This means that loans with more investors than 9 are not considered to be bought by institutional investors. Further, we used the 50th percentile to set the parameter for “loan original amount” at 6 500 USD. This is based on a logical assumption that institutions that invest in loans are on the higher end regarding loan size.

Lastly, we believe it is reasonable to set our parameters for the “Average funding amount” at 2 000 USD (75th percentile). We assume that the 75th percentile is a good fit for separating retail and institutional investors. We believe that the amount is in the higher end for what the average crowd lending retail investor would invest in a single loan but at the lower end for what an institution would invest.

Table 1: Percentiles

Percentile	k	Investors	Loan amount	Avg. Funding amount
25th	0.25	2	4 000	54
30th	0.30	9	4 000	60
50th	0.50	44	6 500	97
75th	0.75	115	12 000	2 000
90th	0.90	216	15 000	11 000

4.3 Empirical strategy

We used several regression models on our divided datasets to better identify the effect institutions have on retail investors in peer-to-peer lending. We believe this is the best strategy as this allows us to analyze the differences between institutions and retail investors. As we have produced two different datasets, we generated five models where we more easily can observe similarities or differences between the two groups.

(1) Summary of statistics
A summary of statistics is a part of descriptive statistics that provides us with the essence of information given in our sample data. This model contains general statistics on the combined institutional investors, retail investors, and both groups. The summary of statistics is our general overview where we can observe the overall differences in interest rates, estimated loss, and standard deviation. The results of this summary will be the base for our research question, with the regressions supplementing our findings.

(2) Linear regression
Next, we performed a linear regression on the institutions and retail investors separately. The lender yield (interest rate) is our dependent variable in this regression. We want to explore what variables affect the lender yield of each group. Consequently, we have three independent variables: the number of investors, loan amount, and estimated loss. We only use the variables associated with the two investor groups for the two regressions. Next, we did the same regressions described above, using the estimated loss as the dependent variable.

(3) Logistic regression

Logistic regression models the probability of a discrete outcome given an input variable (Edgar & Manz, 2017). This regression model is suitable for modeling the relationship between one or more numerical predictor variables. We used a dummy variable to run this regression as our dependent variable. This variable is either 1 or 0. The dependent variable will take a value of 1 if the investor is an institution and a 0 if the investor is a retail investor. Further, as our independent variables, we use the parameters described in 4.2.1, that we used to determine whether the investor was an institution or retail investor. With the logistic regression, we can check to what extent these parameters relate to the probability that the investor is an institutional investor (y=1).

4.4 Vulnerability of the study

Because our research is based on a quantitative approach, we find it necessary to reflect upon the weaknesses of our study and results. Our main weakness is our assumptions to generate a subset of data containing only institutional investors. In our data, we did not know if the investor was a retail investor or an institutional investor. Consequently, we made certain assumptions to sort out retail and institutions. These assumptions were based on previous and shared knowledge, such as investment amount and amount of investors. Because of this, we might have some abnormalities in each investor group, where some of the investors maybe should contain the other group instead.

To address this weakness, we set our parameter restrictions so that the investors who do not fall into the group of institutions are considered retail investors. We also exclude a portion of the population that we cannot clearly identify as either institutional or retail investors. As a result, we end up with the investors we are most confident belong to, institutions or retail investors. On the other hand, we end up with fewer observations weakening the study's robustness. However, we believe there are still enough observations, and it is worth excluding the investors we cannot assign to a group.

5 Main Results and Analysis

In this section, we will present the information and results we got from our models presented in chapter 4.3, and discuss these results in light of our research question.

5.1 Summary of statistics

5.1.1 Findings

Presented in table 2, one can see a summary of the statistics from our sample of institutions investing in 20 534 different loans. Overall, the lender yield the institutions receive on these loans is high, amounting to a mean of 15.17 percent. The lender yield is equal to the interest rate on the loan, less the servicing fees. The standard deviation on the lender yield is 4.66 percent. The standard deviation sheds light on the historical volatility of the lenders' yield. With 4.66 percent, one can argue that there is a low range in what one can expect in interest rate as an institutional investor. The Sharpe ratio is viewed as the return of an investment compared to its risk (Sharpe, 1998). For the institutional investor, the Sharpe ratio is 2.63 (Table 2). The Sharpe ratio shows that the institutional investor has a good risk-adjusted return. One can argue that a Sharpe ratio above 1 is good as this would suggest that the investment yields excess returns relative to its volatility.

In table 2, one can also see the summary of statistics for the retail investors. Our sample of loans retail investors invest in is 28 564. Similar to the institutional investors, one can see in table 2 that the retail investor receives, on average, a high lender yield, amounting to 14.52 percent. The standard deviation for this portfolio of loans is 5.96 percent. As a consequence of the higher standard deviation, the retail investors have a Sharpe ratio of 1.94, notably lower than the institutional investors. However, one could argue that this Sharpe ratio is good as well.

There is clear evidence that institutional investors gain a significantly better yield on their peer-to-peer investments than institutional investors. Mohammadi & Shafi (2017) found that the difference is, on average, 40 basis points without any significant decrease in risk. Our findings support this evidence. We found that, on average, institutional investors get 65 basis points higher lender yield on their loans than retail investors. An essential factor to note regarding the lending yield is its standard deviation. The standard deviation of the lenders' yield for institutions and retail investors is 4.66 and o5.96 percent. One could therefore argue that not only do the institutional investors get a better yield on their loan investment, but they also have a lower spread on the yield, which could imply lower risk. This has a significant impact on the Sharpe ratios for the institutions and retail, where institutions on average get a Sharpe ratio of 2.63 and retail investors 1.94.

Estimated loss is defined as the "estimated annualized loss rate on the loan" (Prosper, 2008). One can also see this as the estimated principal loss on charge-offs. As mentioned in chapter 3.2, higher-risk loans generally have a higher interest rate. The estimated loss rate is published by Prosper when the loan is listed. Consequently, the estimated loss rate can be regarded as the borrower's risk profile. Because of this, estimated loss is an essential statistic in our analysis. Table 2 shows that the average estimated loss institutional investors have on their investments is 6.18 percent, with a standard deviation of 2.80 percent. This means that the institutional investors will have an estimated loss of 6.18 percent of the outstanding debt the creditor has deemed uncollectable. It is essential not to confuse this statistic as a measure of the actual loss the institutions will get on their investments. When the estimated loss is subtracted from the lender yield, one can see the estimated return, which amounts to 8.08 percent.

The loss that retail investors, on average, are estimated to have on the charge-offs is 5.33 percent, with a standard deviation of 3.46 percent (Table 2). With this estimated loss, the retail portfolio gets an average estimated return of 8.92 percent. The estimated return retail investors get on their loans is higher than the institutional investors' loans, but with a higher standard deviation.

Table 2: Descriptive statistics

	Mean	Std. Dev
Institutional investors		
Interest rate Lenders	0.151	0.046
Fundingtime (Days)	9	12
Estimated effective yield	0.142	0.041
Estimated return	0.080	0.017
Estimated loss	0.061	0.027
Amount borrowed (USD)	14 075	5 670
Expected loss	1.29	-
Default rate	0.001	-
Sharpe ratio	2.635	-
Retail investors		
Interest rate Lenders	0.145	0.060
Fundingtime (Days)	16	37
Estimated effective yield	0.131	0.057
Estimated return	0.089	0.031
Estimated loss	0.053	0.034
Amount borrowed (USD)	12 050	6 122
Expected loss	6.17	-
Default rate	0.015	-
Sharpe ratio	1.949	-

5.1.2 Discussion

A critical premise to measure the difference between institutional and retail investors is the risk aspect. Bastani, Asgari, & Namavari (2019) argue that loans with a higher risk will yield a higher interest rate. Tables 3 and 4 show that this is consistent for institutional and retail investors, where there is a positive correlation between estimated loss and lender yield. Estimated loss and standard deviation of lender yield are arguably our best risk measurements for the respective investor groups. Retail investors, on average, have an estimated loss of 5.33 percent, whereas institutional investors have 6.18 percent (Table 2). This implies that retail investors, on average, have a lower loss on their investments than institutional investors. However, it is essential to note that the standard deviation for the institutions is 2.80 percent, while retail investors have 3.46 percent. One can argue that the estimated loss is much more unpredictable for retail investors than for institutional investors. In our opinion, this does not make up for the significant difference in estimated loss between the groups. An interesting aspect of this result would be observing the actual average loss the investor groups take on in their investments, as Prosper determines the estimated loss we are provided.

Loan defaults are an increasing problem for institutions and can affect their operations in terms of liquidity, profitability, and lending capacity (Ntiamoah, Oteng, Opoku, & Siaw, 2014). One could argue that this is an essential measure for institutions when considering investing in any loan. As presented in table 2, one can see that the default rate for loans that institutions invest in is, on average, 0.16 percent. Out of the 20 534 loans that institutions invested in, only 32 loans defaulted. One can argue that this is a low amount compared to the risk profile of many of the borrowers on crowdlending platforms. By multiplying the estimated loss and the default rate, we were able to find the expected loss of the population, which amounted to 1.29.

One can see that the retail portfolio has a default rate of 1.54 percent (table 2). This is notably higher than the institutional portfolio. Out of the 28 564 loans invested in, 439 defaulted. Despite having a higher default rate than the institutional portfolio, one could argue that this is not a very high default rate. Further, we have calculated the population's average expected loss to be equal to 6.17.

Contrary to a traditional bank loan, where the lender gets a deep dive into the personal finance and personalities of the borrower, crowdlending is online-based and does not offer the same financial repercussions. The crowdfunding platform determines the lender rate before the investor decides to invest or not. Because of this, we believe that the default rates for the different groups are an indicative measure. Loan defaults affect operations in terms of liquidity, profitability, and lending capacity (Ntiamoah, Oteng, Opoku, & Siaw, 2014). Therefore, one could argue that a default rate of 0.16 percent is a very low number for institutions and will not affect their operations significantly. One can argue that the default rate for retail investors is not that high either. However, comparing the two default rates, one can see a very large difference. As mentioned in chapter 2, one reason for this difference can be because retail investors do not have the same capacity to analyze and evaluate risks and make good investment decisions as institutions can.

As previously discussed, the estimated loss is determined by Prosper when they post a loan on their page. Subsequently, this number is just an estimation and does not give us any actual information on how much one can expect to lose. In our opinion, the expected loss is a better estimation of the riskiness for the different groups. This can be calculated on the basis that we know how many loans defaulted and the default rate. As mentioned above, one can see that the estimated loss is higher for institutions than for retail investors. Notably, the expected loss is 6.17 for retail investors and only 1.29 for institutional investors (Table 2). When investing in loans with higher risk and estimated loss, one generally gets a higher lender yield (chapter 3.2). However, with these findings, one can argue that even though the institutional investors, on average, invest in loans with both higher lender yield and estimated loss, the actual loss that the institutional investors take on the loans they invest in are significantly lower than the retail investors. We can see evidence of this from both the default rates and the expected loss. We believe these results occur because institutions are better at picking loans with too high an estimated loss. This is consistent with (Cortese, 2014), which states that many fund managers use their own credit approaches to identify loans that may be underpriced or overpriced and cherry-pick the ones they want. The crowdfunding platforms give a higher lender yield when there is a high estimated loss. If the institutions pick out loans where the lender yield is higher than it should be because of a wrongly calculated estimated loss, they can pick loans with high yield and lower risk. One can argue that this might come from algorithmic trading or a better understanding and judging of the asymmetry between the lender and the borrower.

One argument we found to support this narrative is that the institutional investors have better access to algorithmic trading than the retail investors, making faster-acting and better-informed decisions (chapter 3.1). Our analysis shows that institutions have a lower funding time than retail investors. The institutions averaged 10 days to fund the loans, whereas the retail investors spent 16 days. This is consistent with the evidence stating institutions are making faster decisions investing in the loans. Although the institutional investors have a lower funding time than the retail investors, it is important to note that the difference in funding time of 10 days to 16 days is most likely not due to algorithmic trading. As discussed in chapter 2, Wang & Overby (2016) researched the funding time from institutional investors using algorithmic trading. The trading time is usually much lower than ten days using trading algorithms. They found that 10 percent of the loans were funded within 60 seconds, and 30 percent were funded within 10 minutes. They argue that this suggests that these loans were funded using algorithmic trading. With an average funding time of 10 days, one could argue that there is no clear evidence that the average institutional investor used algorithmic trading. However, it does not rule out that a part of the population uses algorithmic trading in their investment strategy.

5.2 Regression

As described in section 4.3, we did two linear regressions on both the retail and the institutional portfolio, with both lender yield and estimated loss as the dependent variable. In this section, we will present our results. When we evaluate our regression models, we will use a t-statistic above 2 or below -2 as a proxy to determine whether our coefficients are useful in our analysis.

5.2.1 Findings

The results of our tests of our linear regression models for institutional investors are shown in Table 3. They are estimated based on the specifications described in 4.3.

In table 3 (1), one can see the regression model where we check the correlation between the lender yield from institutional investors and our independent variables. In table 3 (2), the estimated loss is our dependent variable. The adjusted r-squared from these models are respectively 0.9272 and 0.9264. This indicates that these models are well-fitted, where the independent variables primarily explain the variance in the lender yield and estimated loss. One can also see that every variable has a t-statistic above 3 or below -2, which indicates that the coefficients are significant and useful for our analysis.

When evaluating the coefficient values, it is essential to note that estimated loss is given as a percentage. In contrast, the other variables are given as either an amount of money or as a count of the number of investors. As a result, the variables given as a percentage will naturally have a higher coefficient than those given as a number. Consequently, the estimated loss has a significantly higher coefficient than the other variables.

As presented in table 3 (1), one can see a positive correlation between estimated loss and lender yield. This is consistent with the information described in chapter 4.3, where the investor generally receives a higher yield the more risk they take. This coefficient represents the mean increase of lender yield for every additional one percent increase in estimated loss. If one increases the estimated loss by 1 percent, the average lender yield increases by 1.58 percent. This result is consistent with the outputs presented in table 3 (2), where the estimated loss is the dependent variable. The lender yield coefficient here is 0.582, which again confirms that if one increases the estimated loss, the lender yield will increase by approximately 150 percent.

In the sub dataset created with institutional investors, one parameter specification is that the number of investors must range between one and nine (chapter 4.2.1). Despite these low numbers of investors, one can still see that a slight increase or decrease in the number of investors will influence the lender yield. In table 3 (1), one can see that the investors' coefficient is 0.001. This implies that a loan with only one investor will, on average, receive 1.73 percent less lender yield than a loan with ten institutional investors. In table 3 (2), one can see that the investor coefficient is -0.0008188. Consequently, this implies that when the number of institutional investors investing in a loan increases, the average yield increases while the average estimated loss decreases.

The loan amount regarding yield is the only insignificant independent variable, with a t-statistics of -1.02. This implies that the institutional investors are indifferent about whether the loan amount is high or low. However, as presented in table 3 (2), there is a negative correlation between the loan amount and the estimated loss with a t-statistic of -4.89. This indicates that for every unit increase in the loan amount, the estimated loss decreases by the coefficient -3.04E-07.

The average funding amount has a negative effect on the lender yield, with a coefficient of -5.38e-07 (figure 3 (1)). This implies that one would expect a lower lender yield if one increases the average funding amount. The average funding amount is a product of the total loan amount and the number of investors. Consequently, the increased loan amount would result in a higher average funding amount, leading to a decreased lender yield. At the same time, an increasing number of investors would lead to a lower average funding time, resulting in a higher lender yield. This result is consistent with what was presented above, where a decrease in the loan amount and increased investors lead to an increase in lender yield.

Table 3: Linear regression: Institutions

	(1) Lender Yield	(2) Estimated loss
Lender yield		0.582
		(488.20)
Estimated loss	1.580	
	(488.2)	
Loan amount	-1.61E-08	-3.04E-07
	(-1.02)	(-4.89)
Investors	0.001	-8.19E-04
	(4.77)	(-3.72)
Average funding amount	-5.38E-07	2.30E-07
	(-5.24)	(3.68)
_cons	0.052	-0.024
	(102.82)	(-72.50)
Obs.	20 427	20 427
R-squared	0.9272	0.9264

t statistics in parantheses

As for the regressions regarding retail investors, we use the same dependent and independent variables as for the regression of institutions above. Firstly, we want to present the results for the dependent variable “Lender yield” shown in table 4 (1). We observe that the r-squared is 0.8971, indicating that our model is a good fit for what we aim to test. Further, our t-statistics indicate that all independent variables are significant and impact retail investors' yield. Our dependent variable is affected mainly by the estimated loss. It is shown by the coefficient that the lender yield will increase by 1.79 percent by a 1 percent increase in the estimated loss. Further, we observe that the average funding amount has a t-statistic of 9.20, the second-largest impact factor on the dependent variable. The variables are positively correlated, and the coefficient indicates that the lender yield will increase by 0.01356 percent if the Average Funding Amount increases by 1 USD. In addition, an increase in investors impact the lender's yield positively. The t-statistic is significant, and the coefficient concludes that an increase of 1 investor will contribute to an 0.00356 percent increase in yield. Lastly, the total loan amount is negatively correlated to the yield. A 1 000 USD increase in the loan amount would decrease the lenders' yield by 0.0548 percent.

Secondly, we want to present the results for the dependent variable “Estimated loss” as presented in table 4 (2). The model has an r-squared of 0.8980, whereas all the independent variables are significant. The most impactful independent variable is the “lender yield.” This is no surprise when compared to the results presented above. Further, the second-largest impact on the dependent variable would be the number of investors, with a t-statistic of -11.69. The correlation is negative and concludes that an increase by 1 investor results in a 0.00261 percent reduction in the estimated loss. The average funding amount is also negatively correlated and shows that a 1 USD increase in average funding amount will decrease the estimated loss by 0.00613 percent. Lastly, the only positively correlated variable is the loan amount. It shows that an increase in loan amount by 1 000 USD would increase the estimated loss by 0.0196 percent, with a t-statistics of 4.61.

Table 4: Linear regression: Retail investors

	(1) Lender Yield	(2) Estimated loss
Lender yield		0.493
		(376.65)
Estimated loss	1.798	
	(376.65)	
Loan amount	-5.80E-7	1.96E-07
	(-7.19)	(4.61)
Investors	3.56E-05	-2.61E-05
	(8.32)	(-11.69)
Average funding amount	1.36E-04	-6.13E-05
	(9.20)	(-7.94)
_cons	0.043	-0.125
	(44.54)	(-23.83)
Obs.	18 101	18 101
R-squared	0.8971	0.8980

t statistics in parantheses

5.2.2 Discussion

Our primary focus was investigating the risk and lender yield to determine whether the institutional investors had an advantage in the crowdlending market. A notable pattern from our regression analysis is the pattern between loan amount, lender yield, and estimated loss. As highlighted in Table 3 (1), one can see that institutional investors are indifferent about whether the loan amount is high or low in regards to lender yield. Further, in Table 3 (2), one can observe the negative correlation between estimated loss and loan asking amount. This implies that for an institutional investor, it pays to invest in loans with a high asking amount. The institutional investors get a lower estimated loss by investing in these loans. On the other hand, in Table 4 (1) and Table 4 (2), one can see that retail investors have a negative correlation between the loan amount and lender yield and a positive correlation between the loan amount and estimated loss. Unlike institutions, retail investors investing in loans with a higher loan amount give lower lender yield and higher risk.

It is generally understood that institutions have better possibilities to invest higher loan amounts and have more significant funds available than retail investors. This implies that institutional investors have better access to loans that require a higher loan amount. We believe that this alone is a significant advantage over retail investors. Along with getting the same yields and lower estimated losses on high-amount loans, we believe this is strong evidence that institutions have an advantage over retail investors. Institutional investors will invest and fill these high amount loans uninterrupted by retail investors. This is because retail investors get lower yields and higher estimated loss investing in high amount loans.

5.3 Logistic regression

We have also conducted a logistic regression, introducing a binary dependent variable, "Institution." In the dataset, the variable contains "1" if it has been defined as an institutional investor and "0" if it has been defined as a retail investor. The logistic regression shown in table 5 will help us discover which independent variable essentially impacts whether the dependent variable is an institution or retail investor.

Firstly, our model has shown a good fit, containing a pseudo R2 of 0.9707. Out of the four variables, it is just "Estimated loss" which does not significantly impact the dependent variable. The most significant variable with a z-value of 34.73 is shown to be "Loan amount." This means that the variable contributes to the dependent variable being an institutional investor, which does make sense when considering that institutions have more capital than retail investors.

Secondly, the number of investors contributes negatively to the dependent variable with a z-value of -32.87. This is also expected, as institutional investors, in contrast to retail investors, are more likely to buy more significant portions of their investment objects. The lender yield has also been shown to impact the dependent variable positively with a significant z-value of 3.79.

Table 5: Logistic regression

	(1) Institution
Lender yield	286415.7
	(3.79)
Estimated loss	0.0029
	(-1.11)
Loan amount	1.003
	(34.73)
Investors	0.014
	(-32.87)
_cons	3.37E-09
	(-32.54)
Obs.	51 730
Pseudo R-Squared	0.9707

z statistics in parantheses

5.4 Robustness check and research quality

In this section, we will review the quality of our data material and the overall quality of our research. Not just the study's findings but also the research's rigor must be taken into account. The extent to which the researchers strived to improve the quality of the studies is referred to as rigor. This is accomplished in quantitative research by assessing the validity and reliability of the data (Heale & Twycross, 2015).

As presented in the data section of the paper, we have limited our population by excluding loans that appear uncertain due to the number of investors in terms of defining retail and institutional investors. Initially, we excluded the population of loans that contains investors between the 30th and 75th percentile (9-115 investors).

To evaluate the validity of our findings, we want to exclude every loan between the 25th to the 90th percentile (2-216 investors). This is to ensure we only get the extremes of the population, and what we mean is an essential part of determining which loans institutions buy and which retail investors buy.

The results shown in Table 6 appear to be quite similar to the regression analysis conducted on the original population. For the institutions, the independent variable "Investors" is shown to be insignificant for both the yield and estimated loss, in contrast to the original analysis. However, this is logical as the number of investors allowed in the definition of institutions is reduced from 10 to 2. As the results of the robustness check have shown to be in line with the actual results, we believe the findings are reliable.

Table 6: Linear regression: Robustness check

	(1) Lender Yield	(2) Estimated loss	(1) Lender Yield	(2) Estimated loss
Lender yield		0.460		0.583
		(240.43)		(503.80)
Estimated loss	1.939		1.589	
	(240.43)		(503.80)	
Loan amount	-1.15E-06	4.85E-07	-1.13E-09	-6.08E-07
	(-8.68)	(7.72)	(-0.07)	(-4.00)
Investors	6.35E-05	-3.51E-05	0.002	9.76E-04
	(10.02)	(-11.40)	(1.68)	(1.01)
Average funding amount	2.99E-04	-1.34E-04	-5.93E-07	5.37E-07
	(7.41)	(-6.81)	(-2.35)	(3.52)
_cons	0.029	-0.006	0.050	-0.026
	(13.68)	(-6.34)	(30.56)	(-26.42)
Obs.	6 951	6 951	19 740	19 740
R-squared	0.8985	0.9000	0.9323	0.9322

t statistics in parantheses

6 Conclusion

Institutionalization has great potential to affect the regular retail investor in the crowdlending market, although the effect is driven by institutions outperforming retail investors. To predict the impact of more institutions in the crowdlending market, we identify to what extent institutions outperform retail investors on lending performance, lender yield, default rate, and expected loss.

Institutions get a higher lender yield with a lower standard deviation, leading to a significantly higher risk-adjusted return. Institutions have access to more capital, and we find that institutions are indifferent in what loan amount they invest, whereas retail investors seek out the lower amounted loans. This is because evidence suggests that retail investors get lower lender yield the higher the loan amount is.

On another note, we find that retail investors, on average, have a lower estimated loss on the loans they invest in. As previously discussed, this is just an estimation provided by the crowdlending platform. However, our findings reveal that more loans invested by retail investors default than those invested in by institutions. Combining this with the estimated loss, we find that retail investors have a much worse expected loss. We believe this result is a consequence of institutions being better informed and faster, with some evidence suggests using algorithmic trading. With these advantages enjoyed by institutional investors, we believe they can better pick out loans posted with higher estimated loss than it should be, taking advantage of the information asymmetry between the borrower and the crowdlending platform. With evidence suggesting higher estimated loss gives higher lender yield, institutions can invest in loans with higher lender yield and lower risk. One could also argue that institutions are more diversified than retail investors, reducing the risk even further.

Institutionalization will lead to more institutions in the crowdlending market. We have found evidence that institutions outperform retail investors, where they can get a higher yield with lower risk. With an increasing number of institutional investors, we believe that institutions will invest in the more favorable loans, leaving behind the less favorable loans to retail investors.

As a result of all evidence presented above, we conclude that institutionalization will have a negative effect on the retail investor in the P2P lending market.

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