Discrimination in peer-to-peer lending: an empirical investigation

ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis Financial Economics

28-04-2021

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Access to credit markets is a widely studied subject. Regulators and researchers alike have looked at what influences access to credit and how discrimination leads to imperfections. Having its roots in traditional credit markets like mortgages, this study investigates whether loan terms given to minority borrowers differ significantly from other borrowers on the Lending Club peer-to-peer lending platform. Extending discrimination models to modern peer-to-peer lending is a relatively new concept. For this study, a dataset consisting of loans ranging from 2008 to 2015 is used. Combining loan-specific and state-level data, several regressions have been run to test for both taste-based and statistical discrimination based on loan denials, interest rate, amount of funding, and default rate. Results from these models indicate that some loan terms differ significantly between minority and other borrowers, but there does not seem to be enough of a difference to explicitly state a case of taste-based or statistical discrimination.

Key words: *Credit, credit markets, p2p lending, discrimination, Lending Club*

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

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1 | Introduction

Traditionally, because of their financial expertise, allocating capital was almost always done by established financial institutions (Diamond, 1984). These institutions know how to screen their clients, thus being able to determine their borrower's creditworthiness. However, after the financial crisis in 2008, their shortcomings became clear and trust in the traditional financial system decreased significantly. Current capital requirements proved insufficient, prompting the implementation of Basel III, an extension of the previously installed Basel I and Basel II. With these new regulations came more emphasis on stronger capital requirements, updated risk measurements on risk-weighted assets and higher liquidity ratios. Due to these potent increases in regulations and capital requirements, costs of financing increased, leading to a decline in loan growth (Sútorová & Teplý, 2013). These increasing costs could especially affect smaller borrowers, forcing them to find their supply somewhere else. This, and the help of the internet and numerous technological developments, are a few reasons of an increase in fintech companies: a combination of finance and technology.

Fintech companies can be traced back to the early 1990s (Arner, Barberis, & Buckley, 2015). Some of their innovations include digitalising the banking system, creating blockchain infrastructures, building virtual currencies, mobile payment systems and much more.

Something worthy of note is the way that fintech varies throughout the world. The United States is miles ahead of other countries when looking at total number of fintech companies and investment, by various categories. The second largest country in terms of fintech investing is China, but the distribution is very different. Where, in 2017, the United States has much more fintech companies than China, the amount of funding is not so different: $7.71 billion for 264 fintech firms in the United States, versus $6.92 billion for seven fintech firms in China. Regarding the latter, most of the funding seems to go to the two largest fintech firms of the country, Tencent and Ping An (Deloitte, 2017).

This paper will have its focus on peer-to-peer lending: online platforms where borrowers and lenders are linked to each other, bypassing the traditional intermediaries. Some reasons for using these platforms include small borrowers not being able to obtain funding through traditional institutions, investors looking for a higher return or individuals not wanting to place their trust in the traditional financial system.

A quick glance at the figure below shows that the industry most affected by changes in technology and finance is in fact the consumer banking area.[1]

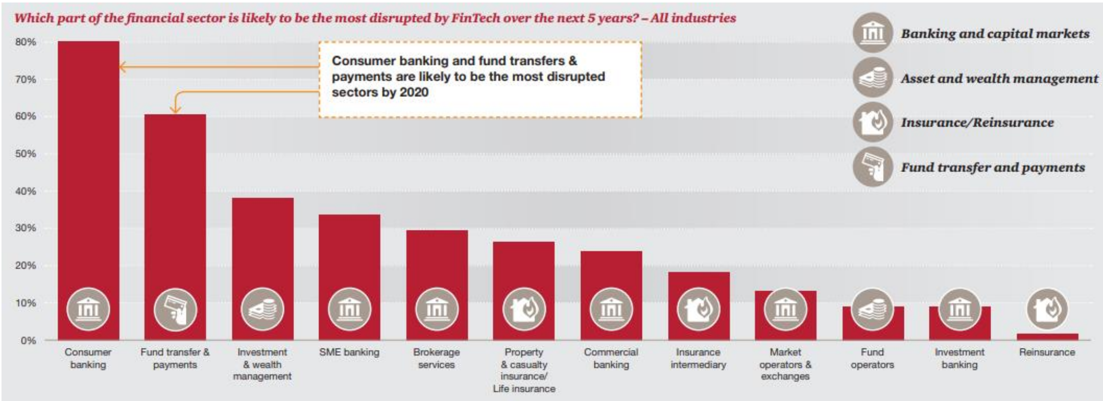

***Figure 1**: A survey where participants were asked which areas of the financial sector are most likely to be disrupted by FinTech developments over the next five years. Source: PwC Global FinTech Survey 2016*

Some large peer-to-peer lending platforms in the U.S. include Prosper and Lending Club. These platforms operate almost entirely online, reducing the need for large buildings and offices, leading to minimal overhead costs. This works in favour of both the borrower and the investor, reducing the interest paid by the former and increasing the rents received by the latter.

Screening applicants could also prove to be more efficient when done by tech-heavy firms. Borrowers know more about themselves and their financial situation than investors do, leading to information asymmetry and adverse selection (Emekter, Tu, Jirasakuldech, & Lu, 2015). These problems could be solved using collateral, but almost none of these platforms oblige their borrowers to provide it.[2] A study by Gambacorta et al (2020) shows that big tech firms could potentially reduce the need for collateral when using extensive statistical models to screen their clients.

Regulation on setting interest rates, however, is an important factor that could potentially raise some questions. How are interest rates determined? Prosper, for example, used to have an auction-like system where interest rates were determined by biddings from lenders that could browse through the loans listed on the platform. However, after increasing competition and regulation,

[1] These forecasts are from a Global Fintech Survey from 2016, as stated in a PWC report called “Blurred Lines: How Fintech is shaping Financial Services”

[2] Peer-to-peer lending platforms Myconstant and Grupeer are some of the few online services that oblige borrowers to provide collateral when opting for loans.

Prosper decided to set the interest rates themselves, based on internal credit ratings assigned to borrowers (Iyer. Et. Al., 2016).

American peer-to-peer lending platform Lending Club uses FICO scores and applicant screening to determine their credit grades, which are then used to calculate an interest rate based on that grade and various borrower characteristics. One could wonder if there are any other factors included in establishing these grades. Applicants must declare their postal codes when applying for a loan. It is entirely possible for applicants that live in less favourable states or areas to receive lower credit grades ex ante.

A study by Harkness (2016) shows that demographic factors like race and gender influence lending decisions. With the use of the peer-to-peer lending platform Prosper, a study is done to show that race and gender have a significant impact on lending decisions.

This kind of discrimination in lending processes could have its roots in the traditional banking system. Screening borrowers and making decisions based on their credentials is essential in establishing loans and interest rates, but making these decisions based on demographic factors that ex ante do not have any significant explanatory power on loan performance should not be acceptable.

A quick glance at a study by Cavalluzzo and Cavalluzzo (1998) shows clear prejudicial discrimination towards Hispanics and some weaker evidence towards Asians regarding loans for small business. African American businesses are significantly less likely to hold loans than businesses owned by white people.

Another sector where discrimination is present is in mortgage lending. Research by Ladd (1998) suggests that statistical discrimination, driven by profits, is apparent in mortgage lending. Loan denial rates are much higher in minority groups.

Based on these findings, it seems obvious that lenders in a variety of credit markets base their loan acceptance on characteristics not necessarily affecting loan performance ex ante. Online marketplace lending, Lending Club in the case of this study, could also be subject to this kind of statistical discrimination. How do they determine credit grades and loan terms? When applying for a loan, applicants must include their geographical data like city and state. Are loan applicants from regions where macroeconomic factors are less desirable ex ante worse off? That is what this research is trying to find out. If there is a case of statistical discrimination based on these macroeconomic factors, we will also look at how these factors are affecting loan performance.

With the help of various regression models, this study will try to answer the following research question:

"On the Lending Club peer-to-peer lending platform, how do loan terms for borrowers from lower ranked states differ from borrowers from high ranked states, given the same credit worthiness?"

This study is organized in the following structure. Section 2 will focus on the theoretical framework, which lays the foundation for the hypotheses. Section 3 explains what kind of data will be used and from where it is obtained. Section 4 discusses the methodology and explains what kind of models are used to answer the hypotheses stated in section 2. In section 5 the results from the statistical models are explained. Finally, section 6 gives a conclusion, and some potential shortcomings or possibilities for further studies.

2 | Theoretical Framework

It seems evident that lending discrimination exists or has existed in the traditional lending systems. To draw meaningful comparisons between marketplace lending and traditional lending, it could be helpful to see how they substitute or complement each other.

The first part of this section will have its focus on literature regarding peer-to-peer lending, how it complements or substitutes the traditional banking system, and its implications. The second part will be about statistical and taste-based discrimination, what its implications are, and how it fits in the (traditional) banking system. The final part will look at to what extent discrimination occurs in existing credit markets.

2.1 | Peer-to-peer Lending

When looking at literature on peer-to-peer lending, numerous studies have been done on different aspects of marketplace lending. Rau (2019) looks at crowdfunding, which resembles peer-to-peer lending in many ways, at a more global level. Instead of looking at loan-level data, he studies crowdfund platforms around the world per country, and tries to find what kind of economic determinants impact the choice of investors to lend money to complete strangers. His study shows that social factors do not really play a significant role in determining crowdfunding volume, while legal factors, ease of starting a platform and profitability of incumbent banks do have a significant effect.[3]

A paper by Iyer et. Al. (2009) uses loan-level data from a peer-to-peer lending platform, Prosper, to study how lenders infer the creditworthiness of borrowers. Aside from standard banking variables, investors also make use of "soft" financial factors like borrower's maximum rate, which proves especially significant in the lower credit categories.

Iyer. Et. Al. (2016) did a follow-up on their previous study on screening borrowers, and find that lenders can predict the borrower's default rate with 45% more accuracy than their credit score. They also reach 87% of the econometrician's predictive power using standard financial variables. Again, the lenders make use of various soft financial variables. These variables include but are not limited to maximum borrower's rate, number of days the loan is listed, what the loan is for, number

[3] Legal factors include variables like Rule of Law, Control of Corruption, Regulatory Quality, Common Law Indicator and Civil Law Indicator.

of friend endorsement, and so on. Their results indicate that even non-expert lenders can screen borrowers very well, especially when using this non-standard information.

When reading these papers, it seems like peer-to-peer lending platforms are taking over the traditional credit supply system. A paper by Tang (2019) did research on a peer-to-peer lending platform, specifically what their contributions are to the traditional banking system. By using a period where there is a negative shock in bank credit supply, he argues that if peer-to-peer lending platforms would be substitutes, and serve the same clientele as banks, borrowers at the lower end of bank quality distribution would switch to peer-to-peer lending because of this reduced credit supply.[4] This would worsen the quality of the peer-to-peer lending pool. If, however, peer-to-peer lending platforms would be complements, borrowers underserved by banks are in this peer-to-peer pool, thus the quality would be lower than that of banks. Due to this credit supply shock, low quality bank borrowers (who still have better quality than those in the peer-to-peer lending pool) would switch to the peer-to-peer lending pool, increasing the quality of the peer-to-peer lending pool. The results from this study indicate that credit expansions provided by peer-to-peer platforms solely benefit infra-marginal bank borrowers, while at the same time being a complement to bank by providing smaller loans to borrowers.

Di Maggio and Yao (2019) also did research on whether fintech lenders serve borrowers underserved by banks, or if they serve high-quality borrowers. Their findings showed that fintech borrowers, prior to their loan origination, have pretty good credit scores and reasonably well financial situations. However, after their loan origination, credit outcomes significantly decrease. The authors argue that instead of improving their financial situations, fintech borrowers actually borrow from peer-to-peer lending platforms to further accommodate their consumption needs. Their credit constraints relax, which often results in borrowing above their means.

A study by Jagtiani and Lemieux (2019) compares fintech loans to traditional loans and finds that consumers with less accurate credit records can still have access to credit because of these fintech loans. These consumers were previously underserved by traditional banks because of their credit ratings, but this research shows that fintech platforms are able to correctly price the riskiness of these borrowers. This has led to a response from traditional banks to start partnering up with fintech platforms.

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[4] This reduction in credit supply was caused by banks tightening their lending criteria. This happened because the FASB implemented new regulation regarding risk-weighted assets for banks in 2010.

2.2 | Economic Discrimination

When speaking of discrimination in an economical sense, the following description is used: "discrimination occurs when members of a minority are treated differently than members of a majority group with identical productive characteristics" (Autor, 2003). Becker (1971) was the first economist that actively explored the economics of discrimination, and divided discrimination in two different types: minority based, or taste-based discrimination, and statistical discrimination.

2.2.1 | Minority-based Discrimination

Becker (1971) mainly did research on taste-based, or minority-based discrimination. This type of discrimination defines discrimination as a situation where workers from a minority group would have to compensate their employers by being more productive for the same wage as the members of majority groups. For a mathematical intuition, we use the model from Autor (2003). In this model, *A* defines a majority group, and *B* defines a minority group. Firms have a taste parameter called *d,* and want to maximize their utility function which is equal to the sum of profits plus the added value of utility from members of specific groups. Firms will choose to maximize the following:

$$U = pF(N_b + N_a) - w_a N_a - w_b N_b - dN_b,$$

Here, p is the price level, F is the level of production, N is the number of workers that belong to a specific group, and w is the wage that is paid to a specific group. Firms that are a priori prejudiced will evaluate the wage of the minority group as wage (w_{mi}) + taste parameter *d.* Thus, they will only hire members from a minority group if $w - w_{mi} \geq d$. This means that there exists a different optimal number of workers that are hired by each firm:

$$\begin{aligned} pF'(N_a) &= w_a, \\ pF'(N_b) &= w_b + d. \end{aligned}$$

In short, minority workers have to increase their productivity at a given wage, or take home a lower wage for the same productivity as workers from a majority group.

2.2.2 | Statistical Discrimination

Statistical discrimination was thoroughly analysed by Arrow (1973) and Phelps (1972). While taste-based discrimination induces a taste factor *d* for firms, statistical discrimination assumes that firms have limited information about applicants. Therefore, firms have an incentive to use characteristics like race or gender to make an estimation about the productivity or quality of applicants. These characteristics can be a noisy signal of productivity, so a risk-averse profit-maximizing firm can be tempted to offer lower wages or positions within the firm.

Again, we make use of the model by Autor (2003). To illustrate the effects of statistical discrimination, we look at two different cases regarding race: case 1, where there is a difference in means between two groups, and case 2, where there is a difference in variance.

In case 1, we assume that the firm is aware of the race of the potential applicant. Applicant *x* can belong to group a or b, and we also have a signal of productivity η. We assume that the firm has learned from past experiences that

$$\begin{aligned} \eta_x &\sim N(\overline{\eta}_x, \sigma^2_\eta) \text{ with} \\ \overline{\eta}_a &> \overline{\eta}_b, \text{ and } \sigma^2_\eta \text{ identical for } a \text{ and } b. \end{aligned}$$

We can immediately see that the applicants belonging to group b are less productive with regards to the mean, but the variance is the same. We can write η_i as $\eta_i = \eta_x + \varepsilon_i$. We assume that the productivity has an error factor, so:

$$\begin{aligned} \tilde{\eta}_i &= \eta_i + \iota_i \text{ where} \\ \iota &\sim N(0, \sigma^2_\iota), \text{ with } \sigma^2_\iota > 0. \end{aligned}$$

From this, it follows that:

$$\tilde{\eta}_i = \overline{\eta}_x + \varepsilon_i + \iota_i,$$

If we want to obtain the expectation of the productivity factor η given the median $\tilde{\eta}$ and *x*, we use the following equation:

$$\begin{aligned} E(\eta|\widetilde{\eta}, x) &= \overline{\eta}_x (1-\gamma) + \widetilde{\eta}\gamma, \\ &= \overline{\eta}_x + (\widetilde{\eta} - \overline{\eta}_x)\gamma. \end{aligned}$$

In this case, $\gamma = \sigma_\iota^2/(\sigma_\eta^2 + \sigma_\iota^2)$, which is the coefficient obtained from the above regression. In this example, $\gamma_a = \gamma_b$, because we assume the variance is the same, so the only difference can possibly be between the mean productivity of a and the mean productivity of b, or:

$$\bar{\eta}_a > \bar{\eta}_b$$

This implies that for a given level of productivity, the firm expects the productivity of the applicants belonging to group b to be below the productivity of applicants belonging to group a.

In the second case, we assume that means of productivity and variations of productivity are the same, but there is more information about one group than the other. This can be caused my firms that have been inaccurate in their information about the ability of the minority group, or the other way around. This indicates that $\sigma_{\iota a}^2 \neq \sigma_{\iota b}^2$. If we take a look at the abovementioned coefficient γ, we find that γ_a is no longer equal to γ_b. This in turn also affects the expected productivity of each applicant belonging to a specific group.

2.3 | Discrimination in credit markets

In the examples above, for simplicity we assumed applicants were only being discriminated on race. But when applying for loans, where it is not needed or given to which race someone belongs, other demographical factors can play important roles. As stated above, when there is a case of statistical discrimination, firms have an incentive to use various characteristics to make an estimation about the quality of an applicant.

Bartlett et al. (2019) make use of mortgage credit risk identification to determine statistical discrimination. When looking at interest rate discrimination, their dependent variable is the interest rate on originated GSE 30-year fixed-rate mortgages, where the regressor is the Latinx-/African American indicator. Harkness (2016) states that traditional factors like credit score and historical financial behavior are not sufficient for determining future behavior and environments. Lenders are likely to also be guided by cultural factors about the borrower’s demographic characteristics.

There have been numerous cases of loan discrimination in traditional banking. Cavalluzzo and Wolken (2005) find that personal wealth factors, like home ownership, are important factors in determining downturn of loans. A paper by Berkovic et. Al. (1998) looks at discrimination in mortgage lending, focusing more on noneconomic factors. The authors use a measure of market concentration to see if loans to minorities perform better than loans granted to non-minorities in less competitive industries and find no statistically significant results to reject no noneconomic discrimination in mortgages.

A study by Boyd (1997) also looked at discrimination in the mortgage sector, and found black people have a much higher rate of default but are also more likely to be discriminated against when trying to apply for a home.

Another way for firms to use borrower characteristics is to look at social media. Niu, Ren & Li (2019) studied how social network information can be used to strengthen predictions of financial firms. They extract social network data from mobile network operators and use a Chinese peer-to-peer lending platform to test if that social network data can be used for credit scoring. With the help of various machine learning techniques, they find that social network variables extracted from phones can improve loan prediction accuracy.

Han (2004) studies the effects of both taste-based and statistical discrimination on factors like loan terms and expected loan performance. He compares loan terms and various measures of expected loan performance for different groups of borrowers, based on certain variables like income and education which represent creditworthiness. In other words: given X (which contains variables that are observable to the lender and the borrower), how do the terms of loans to majority borrowers differ from those to minority borrowers? To answer this question, the author makes a difference between taste-based discrimination and statistical discrimination. When looking at taste-based discrimination, the author creates the following model: Z is a vector of household characteristics (income, education, etc.), g is household's group identity, r_0 is the lender's marginal cost and δ is the lender's psychic cost for dealing with an individual from a minority group. It is assumed the psychic costs increase with the number of interactions and transaction size. If taste-based discrimination were to exist, the price of funding for a minority borrower is higher than that for a majority borrower with the same creditworthiness θ. This is because a higher price of today's consumption leads to a substitute and wealth effect. Both these effects imply that the borrower borrows less today, so the loan size would be smaller. The magnitude of the interest rate should be ambiguous: higher costs should lead to a higher interest, but the smaller loan size reduces the need to set the interest rate high. However, empirical evidence shows that for taste-based discrimination, a higher interest rate also occurs. In conclusion:

1. Taste-based discrimination occurs when, given the same creditworthiness, loans to minority borrowers have smaller sizes, higher expected rates of return, higher interest rates and higher probabilities of default.

When looking at statistical discrimination, the model is as follows: borrowers possess private information about Z and lenders try to obtain additional information to better form estimates on creditworthiness θ. When group identity is correlated with private information to borrowers, the lender uses it as a predictor for private information. Again, the equilibrium loan size increases with creditworthiness. Borrowers with a higher creditworthiness have a higher future income, so they gain from substituting consumption of today with consumption in the future: they borrow more today. However, a larger loan size can also lead to a higher risk of default. Default risk is therefore ambiguous. Expected rate of return is ambiguous, as there is no factor of extra psychic cost of dealing with minorities. After empirical investigation, the author concludes the following:

2. Statistical discrimination occurs when, given the same creditworthiness, loans made to minority borrowers have smaller sizes, but the same expected rate of return. They should have higher default probabilities and higher interest rates.

This study will try to extend the research from Han (2004) and extrapolate it to the peer-to-peer lending platform from Lending Club. To try answering the research question posed in the introduction, the following hypotheses will be tested:

H1: Loans applications from minority borrowers have a higher probability of being denied, given the same borrower characteristics.

H2: Loans from minority borrowers have a higher interest rate, given the same borrower characteristics.

H3: Loans from minority borrowers have a lower funded amount, given the same borrower characteristics

H4: Loans from minority borrowers have a higher probability of being in default, given the same borrower characteristics.

This study will use a unique dataset, consisting of loan level data and state-level data. Instead of using race as minority, state-level demographic factors will be used. Where previous literature has looked at for example loan acceptance and race, this study will go a bit further. For the first part, it will also look at loan acceptance rate and how demographic factors influence those decisions. For the second part, however, it will look at the relationship between those same demographic factors, but the focus will be on how they influence loan terms like interest rate, funded amount, and probability of default.

3 | Data

This section will explain which kinds of databases have been used, why they have been used and where they come from.

For this study, multiple sources of data have been used: marketplace loan-level data from peer-to-peer lending platform Lending Club, the US Bureau of Economic Analysis for state-level data on GDP, the Federal Bureau of Investigation website for state-level crime statistics, the Kaiser Family Foundation for healthcare-related data, the Federal Reserve Bank of St. Louis for data on education and the US Bureau of Labour Statistics for state-level unemployment rates.

3.1 | Fintech Loans

The loan data for this research is acquired from the peer-to-peer lending platform Lending Club. The reasons for choosing this platform are twofold: it is the largest American peer-to-peer lending platform in the world, which makes it easier to extrapolate the results; it is also one of the few platforms that grant public access to their loan data.

The main function of Lending Club is bringing borrowers and investors together to borrow or lend out credit.[5] Borrowers looking for credit can opt for a loan varying between $1,000 up to $40,000 and pay an origination fee to the platform. Investors looking for a way to get a return on their money can loan their credit on the platform, while paying a service fee to Lending Club.

In 2014, Lending Club went to the market and had a very successful IPO, where it was valued at $5.4bn (Alloway, Platt, & Massoudi, 2014). This caused the marketplace lending industry to grow even faster.

Lending Club provides loans from 2007 until the present. When borrowers opt for a loan, they can either choose from a 36-month or 60-month period, where payments are made every month, including interest. Each loan includes multiple characteristics that have to be filled out by borrowers beforehand. These include but are not limited to title and length of employment, kind of home ownership (rent, mortgage or own), annual income, loan purpose and how much they wish to borrow. Applicants also have to declare their postal codes. For an overview of the amount of

[5] Rankings came from https://peer-to-peermarketdata.com/peer-to-peer-lending-north-america/.

loans per state, please take a look at figure 9 in the appendix.

Once an applicant is accepted, he receives a credit grade and an interest rate. According to Lending Club, the credit grade is a result of multiple factors, which include the applicant's credit score and other indicators of credit risk from the applicant's filled out form. Credit grades range from A (best) to G (worst), and have sub-grades ranging from one to five. Once a credit grade is assigned, the final interest rate for a given applicant is the result of adding a base rate of 5.05% (regardless of credit grade) to an adjustment for risk and volatility. This adjustment increases with (sub)credit grades to cover expected losses, and to provide higher risk-adjusted returns for investors (Lending Club, 2020).

For each given loan, there exists a loan status, which Lending Club updates throughout the years. This status describes how the loan currently acts: it can be charged off, current, in default, fully paid, or there can be late payments.

The sample used for this research consists of loans ranging from 2008 until 2015, where a distinction is made for accepted and rejected loans. For the loans that have been accepted, the assigned credit grades have been calculated by Lending Club itself. For an overview of how Lending Club credit grades are calculated, please take a look at table 7 in the appendix.

3.2 | State-level economic factors

Lending Club does not provide racial data on applicants, so there must be another way to state which individuals belong to a minority group. However, the dataset provided by Lending Club includes the states where the applicants live in. This makes it possible to merge state-level data, obtained from various sources, with the existing Lending Club dataset. This way, we can make a distinction between welfare of various groups.[6]

GDP on state-level is obtained from the US Bureau of Economic Analysis. The BEA is one of the world's leading statistical agencies, which publishes economic statistics to the public. It gives out data regarding national, regional, industry and international industries on factors like growth, development, and positions in the world economy.

6 Geographical factors are based on the state rankings by usnews.com. They rank states based on a wide variety of categories, but for the sake of this study, only the following have been chosen: GDP, crime, unemployment rate, educational attainment and healthcare.

Crime-rate statistics come from the Federal Bureau of Investigation (FBI) website. The FBI is the security and intelligence organization dealing with counterterrorism, criminal investigation, and national security for the United States. From their database, total amount of arrests per year per state have been collected. Dividing this by the population per state gives us a rough crime-rate statistic.

The state-level unemployment rates were obtained from the US bureau of Labor Statistics. This bureau is a government statistical resource that serves the US Federal Statistical System. It provides statistical data on prices, (un)employment, compensation, and productivity.

Educational attainment data per state comes from the Federal Reserve Bank of St. Louis. They produce high-quality data in the areas of macroeconomics, money and banking, and applied macroeconomics. To measure educational attainment, the percentage of people with a bachelor's degree or higher has been used.

Finally, to measure healthcare, the amount of people that have health insurance has been taken. This comes from the Kaiser Family Foundation, a non-profit organization and leader in health policy analysis. They offer various databases on demographics and health-related factors in the United States.

3.3 | Data Description

An important factor of receiving credit through online marketplace platforms like Lending Club is how easy and quickly loans can be given out to applicants. One of the pieces of information borrowers need to explain, is the loan purpose when applying for credit.

As previously stated, a lot of borrowers make use of peer-to-peer lending platforms because of being underserved by the traditional banking system. Di Maggio and Yao (2019) argue that borrowers using peer-to-peer lending platforms actually worsen their financial situations, by borrowing more to pay off their current debts, which inevitably leads to even more debt.

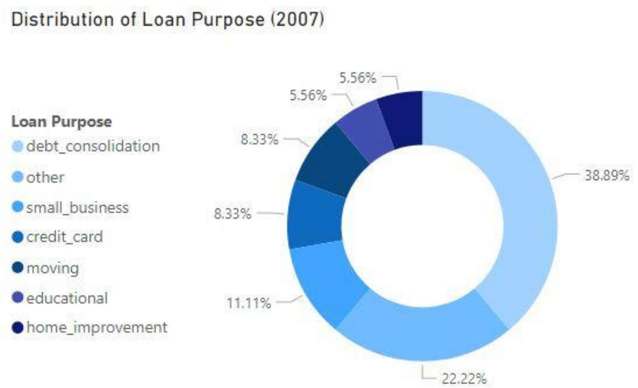

***Figure 2**: Loan purpose distribution in 2007.*

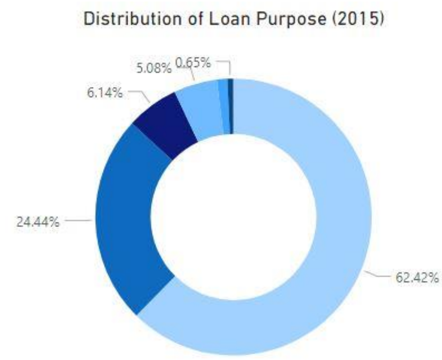

***Figure 3**: Loan purpose distribution in 2015.*

Looking at figure 2, this seems to be the case here as well. In 2007, when Lending Club first started lending out money through their platform, most of the borrowers seemed to apply for a loan in order to pay off debt. Roughly 40% borrowed credit to pay off existing debt and around 8% used it to pay off credit card debt. According to figure 3, in 2015 roughly 61% borrowed credit to pay off existing debt, whereas almost 25% used it for to pay off credit card debt. This is quite a steep increase regarding loan purpose.

This could prove to be one of the pitfalls of online marketplace platforms: instead of lending out credit to customers underserved by banks, debt they already have just seems to accumulate even more. Paying off current debt with new debt obtained via peer-to-peer lending does not seem to be a healthy way of increasing household financial stability.

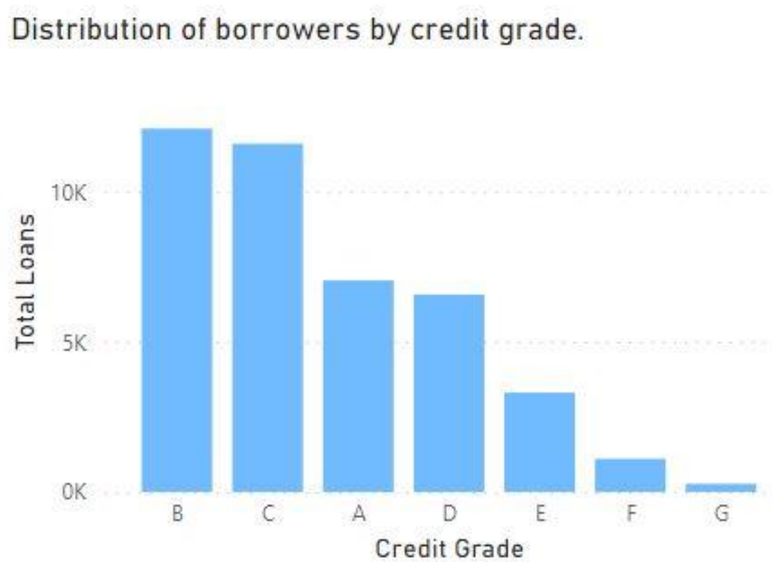

***Figure 4**: Distribution of loans by credit grades.*

Figure 4 shows the distribution of the dataset, based on the credit grades. It seems to be skewed to the right, which indicates that the mean of the sample is to the right of the median. Most of the borrowers in this dataset have a credit grade of B or C, which is not so risky. A and D are also common, while riskier credit grades like E, F or G are much less frequent.

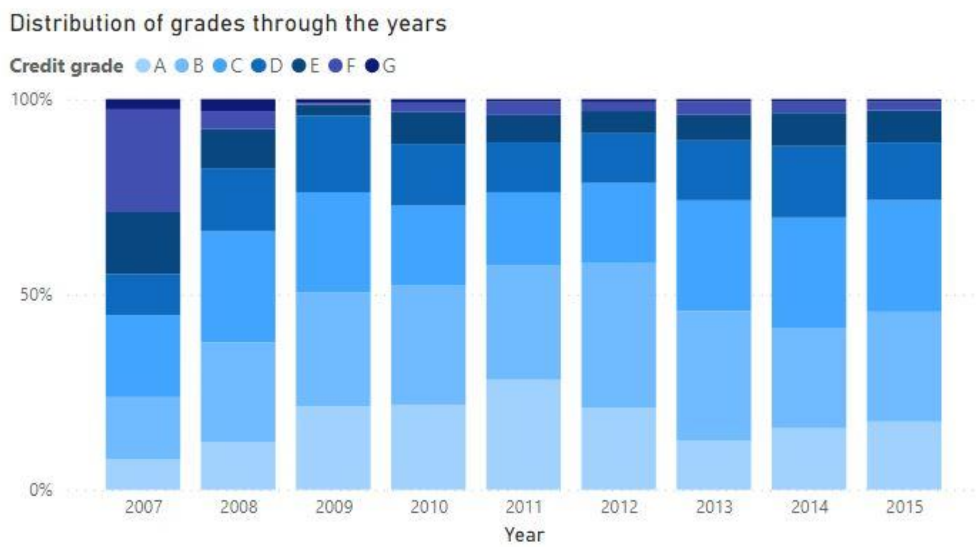

Figure 5*: The distribution of credit grades throughout the years.*

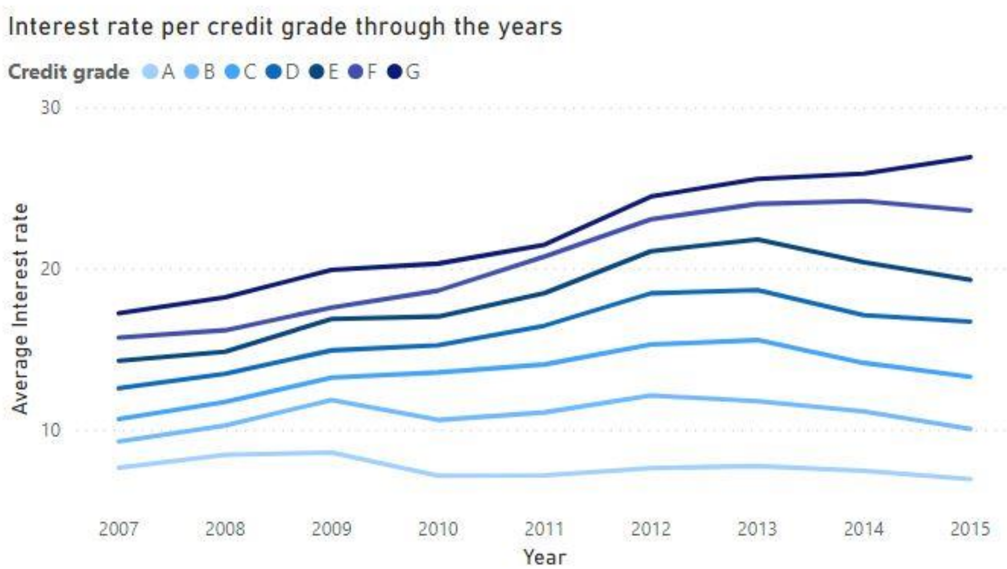

Figure 6*: The Interest rate throughout the years, per credit grade.*

From figure 5 we can see that throughout the years, loans originating from Lending Club have become relatively less risky. Starting in 2007, a larger part of the loans consists of borrowers with higher credit grades. As time increases, credit grades in the range of E-G become less frequent.

Looking at figure 6, it is clear that the average interest rate on loans increases throughout time. As mentioned before, Lending Club has a base rate of 5.05% per loan, regardless of credit grade. The assigned credit grade should increase the total interest rate, with higher added interests on increasing (sub)credit grades. However, apart from credit grade A, the interest rates on these loans increases throughout the years, even though the credit grade stays the same. One reason for this could be an increase in subgrades. For example, a subgrade of A3 has a higher interest rate than a subgrade of A1. Thus, when looking at the figure, it could be the case that there simply are more borrowers with higher subgrades than before. Unfortunately, this difference between subgrades is the highest for the lower, less risky credit grades. If we take a look at credit grade G, the subgrade difference between G1 and G5 is 0.2%. The subgrade difference between A1 and A5 is 2.53%, which is a much higher difference. There seems to be another reason for the increase in interest rates.

4 | Methodology

This section will look at the used methodology for this study and which models are used to determine if there could be a case of discrimination in the lending data.

4.1 | Creating the minority groups

In order to see if there are any significant differences on loan terms between minority and majority groups, we need to create an indicator for belonging to a minority group. Every loan consists of loan specific data and borrower characteristics, including year of origination and the state where the borrower lives. Using the state-level demographics, we can create groups based on these factors. This way, every borrower falls into a specific group.

As mentioned in the previous section, the state-level demographics consist of GDP, unemployment rate, education, healthcare, and crime.

	State-level factors		
Variable	Mean	Min	Max
GDP	892793	27113	2559643
Unemployment Rate	6.3	3.0	13.7
Educational attainment	0.31	0.17	0.41
Healthcare coverage	0.88	0.76	0.97
Crime rate	0.03	0.0003	0.075

***Table 1**: State-level demographics*

In table 1 the descriptive statistics from the state-level demographics are shown. These state-level factors have been normalized and scaled to put equal weight on them. Next, the scaled factors are added together to create one variable. For this study we assume GDP, education, and healthcare count towards a better region, while unemployment rate and crime rate do the opposite. Afterwards, terciles have been created to make sure every individual loan belongs to a specific "group". Group one belongs to the lowest tercile, where the loans are from the worst states. Group two belongs to the middle tercile, and group three to the tercile where the best states are. This is done separately for each year. Else, if there were to be growth for all states throughout the years, creating groups based on terciles would not make sense, since all states from earlier years would then belong to group one. By doing it separately for each year, we control for any yearly changes. Now we have three distinct groups based on these factors, so we can see if there are statistical differences between them, holding borrower characteristics constant. For the correlation matrix between state-level factors and borrower characteristics, please take a look at table 8 in the appendix. In the following regressions, two group dummies are included: a dummy for belonging to group one, and a dummy for belonging to group two. This is in line with the research from Han (2004), where dummies are used to indicate if a borrower belongs to a minority group black or a minority group Hispanic. The benchmark here is majority group, which in this case is a person belonging to group three, where the best borrowers belong to. Finally, for all the following regressions, logs have been taken for the variables funded amount, applied amount and personal income. This is in line with research by Lütkepohl and Xu (2010), who state that taking logs stabilizes variance.

4.2 | Loan denials

The loan data from Lending Club consists of two different datasets: one where all the loans are accepted and have been given loan terms, and one where loans are stored that have been denied. To determine what influences the denial rate, both datasets have been merged.

For the first part of this study, the dependent variable is whether a loan is accepted or not: a binary variable, which can be either one or zero. When the dependent variable is not continuous, but binary or categorical, it is insufficient to use a simple linear regression model. The residuals from the linear probability model violate homoscedasticity and normality of the assumptions of errors, which leads to invalid standard errors. A probit model could be a solution but implementing the odds from a logistic regression is more intuitive.

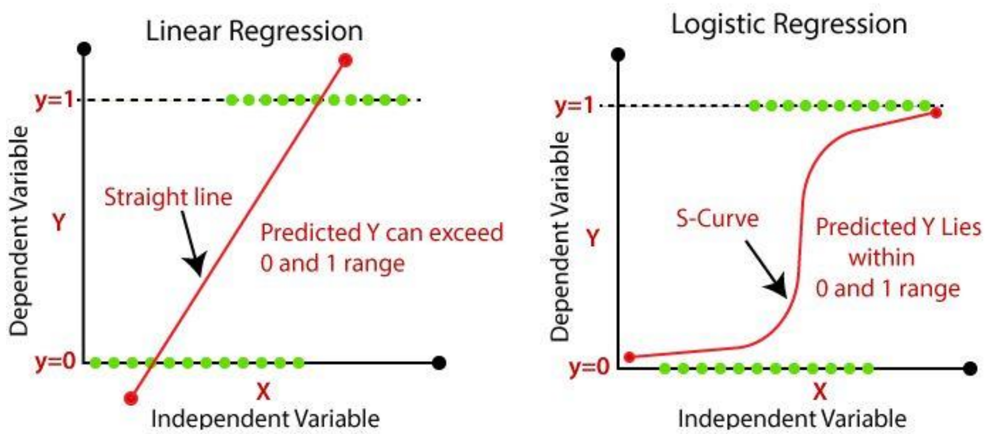

Figure 7*: Linear Regression and Logistic Regression with a binary dependent variable.*

In figure 7, a schematic overview is shown of two different regressions with a dependent binary variable. On the left side, a simple linear regression is used to forecast the probability of the independent variables to affect the dependent variable. However, the probabilities exceed the range of 0-1, which is not something we want. On the right side, a logit model is shown, which solves the problem of reaching values greater than one or smaller than zero.

$$\Pr(y_j \neq 0 \mid \mathbf{x}_j) = \frac{\exp(\mathbf{x}_j\boldsymbol{\beta})}{1+\exp(\mathbf{x}_j\boldsymbol{\beta})}$$

Figure 8*: Mathematical explanation of the logistic regression.*

For a more mathematical approach, please take a look at figure 8. Here, x_j describes the respective explanatory variable with β as the respective coefficient. Instead of using the least-squares as used in a linear regression, the likelihood of belonging to a positive outcome of a binary variable is computed, which in this case is loan denial. This model follows a binomial distribution.

The dependent variable in the first study is loan denial, which can take a value of one or zero: one means that a loan is denied, while a value of zero means that a loan is accepted. The logit regression will take the following form:

$$ln\frac{P(y_i)}{1-P(y_i)} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + U_{it} + \varepsilon_{it}$$

On the left side, we have the log odds of the dependent variable, which in this case is the odds that a loan is denied (loan denial = 1). On the right side, we have the constant β_0, followed by the borrower specific variables and the group they belong to. These are respectively length of employment, household debt-to-income, their fico score, the amount they asked for, a dummy for group one and a dummy for group two. These factors are followed by the control variables U and ε, the error term. For simplicity, we assume these borrower specific variables to be a good proxy for creditworthiness.

4.3 | Interest rate & funded amount

This part will look at the loan dataset where only accepted loans are given. This makes sense, since it is not possible to assign interest rates to loans that have been denied. For this part, an ordinary least squares regression is used to determine whether belonging to the minority group leads to a higher interest rate. In this case, OLS is sufficient since the dependent variable interest rate is continuous. This regression will be the following:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + U_{it} + \varepsilon_{it}$$

On the left side, the dependent variable is interest rate, which we assume is linear. On the right side, the borrow characteristics are as follows: length of employment, annual income, debt-to-income, fico score, and group indicator.

A simple ordinary least squares regression is also used for the regression with funded amount as dependent variable, which looks like the following:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + U_{it} + \varepsilon_{it}$$

The only difference with the previous regression is the dependent variable. The independent variables are the same.

4.4 | Default

Lending Club includes loan status with every loan on their platform. Loans can be fully paid, in default, late with payments, or charged off. For this regression, both charged off and default are considered to be in default. The only difference between a loan being in default and charged off is that when a loan is charged off, it is certain it will not be paid back. When a loan is in default, there have been multiple late payments, so the odds of that loan being charged off in the future is high. We create a binary variable where default takes a value of 1 and fully paid takes a value of zero. Again, we make use of a logistic model since the dependent variable is binary. The regression will take the same form as for the denial part:

$$ln\frac{P(y_i)}{1-P(y_i)} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + U_{it} + \varepsilon_{it}$$

On the left side, we have the log odds of the dependent variable default. On the right side, we again have the borrower specific variables.

5 | Results

This section will present the empirical evidence on the models proposed in section four. Here, we will look at how and if the loan terms given to borrowers from lesser states in the United States differ from those living in relatively better ones. If this is the case, we then look if there could be a case of statistical or taste-based discrimination.

5.1 | Summary statistics

	Denial Rate			Interest Rate		
	No. of Obs.	Mean	Std. Dev.	No. of Obs.	Mean	Std. Er.
Group 1	79484	0.7989	0.4008	14898	13.1762	4.4238
Group 2	69416	0.8067	0.3949	12533	13.1772	4.4051
Group 3	67753	0.815	0.3883	11669	13.0348	4.4131
All	216653	0.8064	0.3951	39100	13.1343	4.415

	Funded Amount			Credit Grade		
	No. of Obs.	Mean	Std. Er.	No. of Obs.	Mean	Std. Er.
Group 1	14898	14466.8412	8364.4741	14898	2.7735	1.318
Group 2	12533	14502.8664	8311.3326	12533	2.7515	1.3113
Group 3	11669	14802.6823	8476.1234	11669	2.7237	1.3009
All	39100	14578.617	8382.094	39100	2.7516	1.3109

	Default		
	No. of Obs.	Mean	Std. Er.
Group 1	14898	0.1831	0.3868
Group 2	12533	0.1779	0.3824
Group 3	11669	0.1779	0.3825
All	39100	0.1799	0.3841

Table 2*: Average loan denials and loan terms*

Table 2 shows denial rates for all loans and the average loan terms for loans that have been accepted. When looking at the denial rates, there is not a clear indication that there is a higher rate of denied loans for areas that belong to the worse group. Controversially, belonging to a higher group seems to resonate with a higher chance of your loan appliance being denied. However, when looking at the interest rate, there seems to be a clear indication that higher groups have a lower interest rate. The same goes for credit grades, which range from one to seven, where one represents a grade of A and seven represents G. The average funded amount seems to be increasing for loans belonging to a better group. As expected, the chance of the loan being in default or charged off is lower for loans belonging to group two and three. Except for the denial rate, all the variables we are interested in seem to behave as expected. For descriptive statistics on all variables used, please take a look at table 8 and 9 in the appendix.

5.2 | Difference in loan denials

When looking solely at the differences in means across the groups, it was clear that borrowers belonging to group one are less frequently denied a loan on the Lending Club platform, in contrast with expectations. Table 3 reports the coefficients from the logistic regression, where the dependent variable is Denied.

	Dependent variable: Denials	
	Coefficients	Odds
emp_length	-0.4051***	0.666907
	(0.002)	
log_amount	0.4957***	1.641670
	(0.007)	
dti	-0.0124***	0.987684
	(0.001)	
fico_score	-0.0030***	0.996980
	(9.49e-05)	
group_1	0.1120***	1.118469
	(0.016)	
group_2	0.1834***	1.201260
	(0.017)	
Observations	216653	
Pseudo R-squared	0.3194	
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

Table 3*: Regression (Logistic Regression) results where loan denial is the dependent variables. Column one shows the independent variables, column two the coefficients and column three the odds.*

In this table, two results are shown: the coefficients and the odds ratios. These outcomes include both accepted and denied applicants, where denial is equal to one if the loan has been denied.

The first coefficient, length of employment, has a negative effect at a statistically significant level of 1%. The odds ratio shows that an increase in length of employment decreases the odds of the application being denied. The reverse is true for the requested amount. It is also significant at the 1% level, but a higher requested amount increases the odds of the loan application being denied. Both debt to income and fico score are also significant at the 1% level but have a small negative effect on the odds of being denied a loan. A higher fico score means a better rate of creditworthiness, so it makes sense that a higher fico score leads to a lower chance of the loan being denied.

The dummies for belonging to group one and group two are also significant at the 1% level. Looking at the odds ratios, belonging to either group one or group two increases the odds of the application being denied. It is vital to understand that this is only in comparison to borrowers belonging to the best group, which is group three. This group is seen as the benchmark. So, in other words, the probability of being denied a loan is higher for group one and two, compared to the benchmark group three.

5.3 | Difference in loan terms

After looking at both denied and accepted loans, it is now time to look at the loan terms given to loans that have been accepted. Table 4 shows the coefficients from the linear regression with interest rate as dependent variable.

Dependent variable: Interest Rate	
	(1)
emp_length	-0.0149***
	(0.006)
log_income	2.1112***
	(0.034)
dti	0.1222***
	(0.003)
fico_score	-0.0182***
	(0.001)
group_1	0.2974***
	(0.054)
group_2	0.3416***
	(0.056)
Observations	39100
R-squared	0.900

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

***Table 4**: Regression results with Interest Rate as dependent variable.*

Length of employment has a negative effect at the 1% significance level. This indicates that a higher length of employment leads to a lower interest rate. This makes sense since a borrower with more years of working experience probably has a more stable financial situation. Level of income, however, has a positive effect at the 1% significance level. This seems counterintuitive, as we expect a higher income to lead to a lower interest rate. Debt-to-income is also positive at the 1% significance level, while fico score is negative at the 1% confidence level.

Looking at the dummies for group one and two, both coefficients are positive at the 1% significance level. Compared to the benchmark group three, it seems evident that belonging to group one or group two leads to a higher interest rate, while controlling for borrower-specific characteristics.

Below, table 5 shows how the coefficients for the linear regression with the funded amount as dependent variable.

	Dependent variable: Funded Amount
	(1)
emp_length	0.0029***
	(0.001)
log_income	0.6905***
	(0.004)
dti	0.0140***
	(0.000)
fico_score	0.0021***
	(7.1e-05)
group_1	0.0068
	(0.007)
group_2	-0.0014
	(0.007)
Observations	39100
R-squared	0.996

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5*: Regression results with Funded Amount as dependent variable.*

Length of employment is positive at the 1% significance level, which means that a higher length of employment leads to a higher amount of funding. Income is also positive and statistically significant at the 1% level. The same goes for debt to income and fico score.

The dummies for group one and group two, however, are not significant at all. Belonging to group one seems to lead to a slightly higher amount of funding, while belonging to group two has the opposite effect. This is in comparison to belonging to group three. Since both dummies are not significant, it is not possible to draw any meaningful conclusions regarding the effect of belonging to group one or two on amount of funding.

Finally, table 6 looks at how default differs across groups. Again, this is a logistic regression where the dependent variable is default.

	Dependent variable: Default	
	Coefficients	Odds
emp_length	-0.0047	0.995307
	(0.004)	
log_income	0.1557***	1.168419
	(0.021)	
dti	0.0349***	1.035506
	(0.002)	
fico_score	-0.0056***	0.994431
	(0.000)	
group_1	0.0147	1.014817
	(0.033)	
group_2	0.0104	1.010419
	(0.034)	
Observations	39100	
Pseudo R-squared	0.02012	
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

Table 6*: Regression (Logistic Regression) results where default rate is the dependent variable. It has a value of 1 when a loan has defaulted and a value of 0 when it is fully paid*

Length of employment has a negative effect on the probability of default, but this effect is not significant at any level. A higher level of income seems to increase the odds of a loan being in default. This is significant at the 1% level. The same goes for debt-to-income. Fico score seems to have a negative effect at the 1% significance level, where the odds of a loan being in default decrease.

Once again, the coefficients for the group dummies are positive, but not significant at any level. Thus, it is not clear if there is an effect of belonging to group one or two on loan defaults, compared to the benchmark.

5.3 | Discrimination in peer-to-peer lending

As stated in the theoretical framework, there are two different kinds of discriminations: taste-based and statistical discrimination. Taste-based discrimination deals with the fact that lenders have some kind of psychological costs that comes with dealing with a certain kind of minority borrowers, which should lead to a higher expected rate of return. Statistical discrimination occurs when lenders do not know everything about the borrowers, so they apply group statistics to individuals. Since expected rate of return is not available, the focus will be on statistical discrimination.

For the first part, we looked at both accepted and denied loans. Looking at table two, it is immediately evident that, overall, much more loans are denied than accepted. In section two, the first hypothesis was stated as follows: "Loans applications from minority borrowers have a higher probability of being denied, given the same borrower characteristics". Based on the results from table three, borrowers belonging to group one and group two have higher odds for their application to be denied compared to the benchmark group three, while controlling for the borrower specific variables. These results are significant at the 1% level, so we cannot reject the first hypothesis.

For the second part, we looked at only the accepted loans and how their terms vary across groups. The following hypotheses were stated:

1. Loans from minority borrowers have a higher interest rate, given the same borrower characteristics.
2. Loans from minority borrowers have a lower funded amount, given the same borrower characteristics.
3. Loans from minority borrowers have a higher probability of being in default, given the same borrower characteristics.

Based on the results in table 4, we see that the interest rate for loans from the minority group is lower, while holding the borrower characteristics fixed. This means we cannot reject the second hypothesis. We can also see from table 5 that funded amount is not lower for borrowers belonging to the minority group, this effect is also not statistically significant, so we must reject the third hypothesis. Finally, the last hypothesis must also be rejected, as the borrowers belonging to group one and two do not have a statistically significant effect on defaults compared to group three. Due to some of the results not being statistically significant, it is not clear enough to state a case of statistical or taste-based discrimination.

6 | Conclusion

The final section of this study will provide the conclusions for this research and try to give an answer on the research question posed in section 1. Afterwards, limitations and suggestions for potential further research will be discussed.

6.1 | Main conclusions

This study tried to find if there were cases of taste-based or statistical discrimination on the peer-to-peer lending platform from Lending Club. This study serves as an extension on the paper by Han (2004), who tried to find cases of discrimination in mortgage markets. Finding cases of discrimination leads to the following question: how do loan terms differ between borrowers from a minority group and from a majority group with the same creditworthiness? To answer this question, multiple regressions have been done to see if there were any statistical differences. Borrowers have been put into three categories based on state welfare factors like GDP, unemployment rate, healthcare coverage, crime rate and level of education. Afterwards, we checked for statistical differences between these groups based on various loan term variables, while holding the borrower creditworthiness variables constant. These loan terms include probability of denial, interest rate, funded amount and default rate. Borrower creditworthiness is explained by their income, debt-to-income, length of employment and fico score. This way, it is shown if an individual from a group with less than desirable state welfare factors receives worse loan terms, even though his or her creditworthiness is the same as an individual from better regions.

In the first part, we looked at both accepted and denied loans to see if individuals from bad regions are denied more often. The results were clear enough to accept this hypothesis.

The second part focussed on only the accepted loans to see how given loan terms differ between individuals. While some loan terms seem to be statistically different for individuals belonging to worse regions as opposed to individuals from better regions while holding their creditworthiness fixed, this was not the case for all loan terms as stated in the hypotheses from section two. While there are definitely some loan terms that have significant differences, these are not enough to result in a case of taste-based or statistical discrimination.

6.2 | Limitations and further research

Looking at the data used for this research, some limitations come to mind. Some variables from the Lending Club dataset were interesting to add to this research, but due to too much missing values, they had to be dropped. Some examples include but are not limited to amount of interest payments, the size of those payments, and number of delinquencies. Especially number of delinquencies could be a good indicator for borrower quality. This study has limited loan status to either charged off, current or fully paid, solely due to the number of missing variables.

Some peer-to-peer lending platforms, like Prosper, provide their own expected rate of returns and expected loss rates. Unfortunately, Lending Club does not, so rates of return have to be calculated manually. Lending Club also does not provide information on borrowers regarding race or gender, so looking for potential discrimination can be a difficult task. Furthermore, it could be the case that some variables like GDP, income and debt-to-income lead to an increased chance of multicollinearity. This could influence the regression results in a bad way. This needs to be taken into account when trying to interpret the results from these regressions.

For future research, more state-level variables could be added to more accurately determine the actual welfare of each state. Also, the data used for this research comes from Lending Club, which is solely based in the United States. Without doing research on peer-to-peer lending platforms in for example Europe or Asia, it may be difficult to extrapolate the results from this study. Finally, it would be better to include more variables that deal with the creditworthiness of each borrower. These factors play an important role, since we want to look for differences while holding these variables constant. Due to restriction specific to Lending Club, more variables could not be added.

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8 | Appendix

Appendix A

LOAN GRADE	SUB-GRADE	LENDING CLUB BASE RATE	ADJUSTMENT FOR RISK & VOLATILITY	INTEREST RATE
A	1	5.05%	3.41%	8.46%
	2	5.05%	3.97%	9.02%
	3	5.05%	4.51%	9.56%
	4	5.05%	5.14%	10.19%
	5	5.05%	5.76%	10.81%
B	1	5.05%	8.28%	13.33%
	2	5.05%	8.97%	14.02%
	3	5.05%	9.66%	14.71%
	4	5.05%	10.35%	15.40%
	5	5.05%	11.03%	16.08%
C	1	5.05%	12.25%	17.30%
	2	5.05%	13.19%	18.24%
	3	5.05%	14.07%	19.12%
	4	5.05%	14.90%	19.95%
	5	5.05%	15.69%	20.74%
D	1	5.05%	17.57%	22.62%
	2	5.05%	19.50%	24.55%
	3	5.05%	22.00%	27.05%
	4	5.05%	24.60%	29.65%
	5	5.05%	25.94%	30.99%
E	1	5.05%	23.85%	28.90%
	2	5.05%	23.87%	28.92%
	3	5.05%	23.90%	28.95%
	4	5.05%	23.92%	28.97%
	5	5.05%	23.95%	29.00%
F	1	5.05%	24.30%	29.35%
	2	5.05%	24.64%	29.69%
	3	5.05%	25.12%	30.17%
	4	5.05%	25.60%	30.65%
	5	5.05%	25.70%	30.75%
G	1	5.05%	25.74%	30.79%
	2	5.05%	25.79%	30.84%
	3	5.05%	25.84%	30.89%
	4	5.05%	25.89%	30.94%
	5	5.05%	25.94%	30.99%

Table 7*: Description of how credit grades are calculated, according to Lending Club*

Appendix B

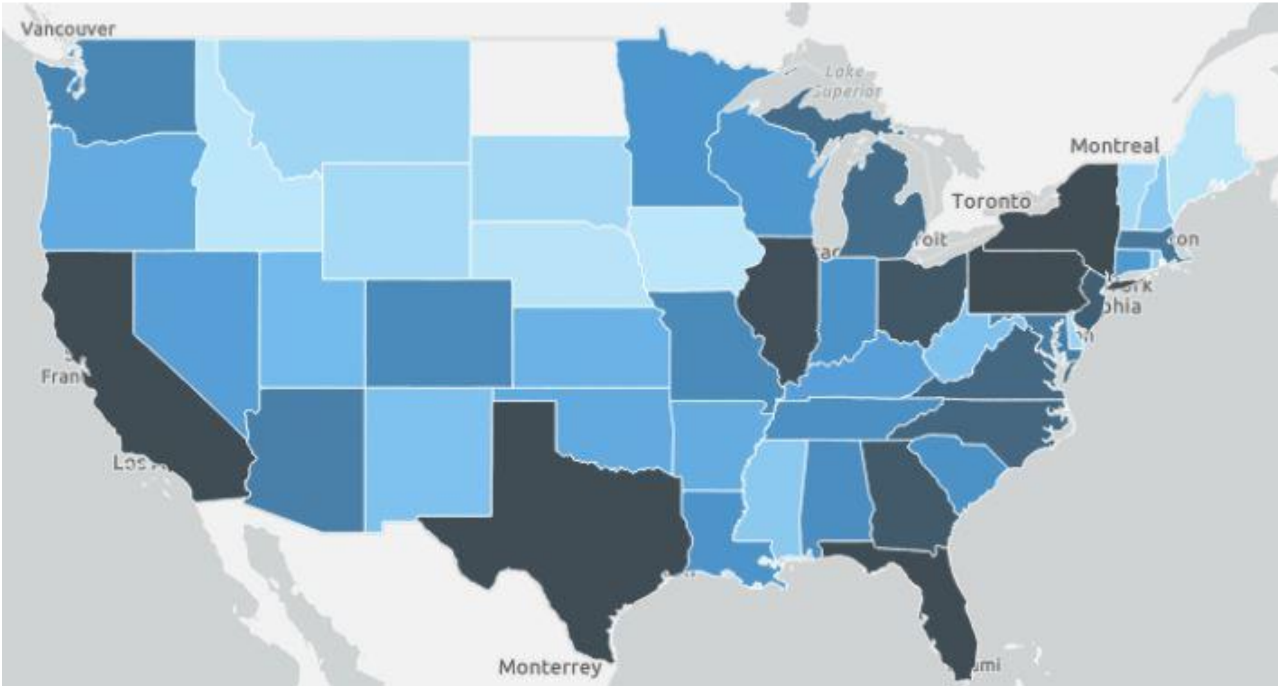

***Figure 9**: Overview of amount of loans per state, where a darker colour blue corresponds to a higher amount of loans.*

Appendix C

Correlations

Variable	Emp Length	Annual Income	Dti	Fico Score	GDP	Unempl. Rate	Health Care Cov.	Education level	Crime rate
Emp Length	1	0.13	0.04	0.02	-0.02	-0.02	0.03	-0.01	-0.03
Annual Income	0.13	1	-0.22	0.12	0.07	-0.04	0.03	0.1	-0.04
Dti	0.04	-0.22	1	-0.04	-0.06	-0.13	0.04	-0.07	0
Fico Score	0.02	0.12	-0.04	1	-0.01	0.06	-0.03	-0.01	0.01
GDP	-0.02	0.07	-0.06	-0.01	1	0.14	-0.14	0.22	-0.15
Unempl. Rate	-0.02	-0.04	-0.13	0.06	0.14	1	-0.43	-0.15	0.12
Health Care Cov.	0.03	0.03	0.04	-0.03	-0.14	-0.43	1	0.47	-0.46
Education level	-0.01	0.10	-0.07	-0.01	0.22	-0.15	0.47	1	-0.31
Crime rate	-0.03	-0.04	0	0.01	-0.15	0.12	-0.46	-0.31	1

Table 8: *Correlation matrix for borrower characteristics and state-level factors.*

Appendix D

Descriptive statistics for denied loans					
Variable	Obs.	Mean	Std. Dev.	Min	Max
GDP	174712	837392	711430	25667.8	2.56e+06
Unemployment Rate	174712	6.9	1.56	3.0	13.7
Education	174712	29.9	4.51	17.1	41.5
Healthcare coverage	174712	0.87	0.04	0.76	0.97
Crime Rate	174712	0.03	0.01	0.00	0.08
Amount requested	174712	12847	10613	500	70000
Year	174712	2013	1.35	2008	2015
Fico score	174712	635	67.5	300	990
Debt-to-income	174712	2.633	83.2	-0.01	14232
Employment	174712	0.82	2.30	0	10
Population	174712	1.45e+07	1.12e+07	516100	3.83e+07

Table 9*: Descriptive statistics for denied loans.*

Appendix E

Descriptive statistics for accepted loans					
Variable	Obs.	Mean	Std. Dev.	Min	Max
GDP	41941	837392	759244	27113	2.55e+06
Unemployment Rate	41941	6.3	1.51	3.0	13.7
Education	41941	30.7	4.49	17.3	41.5
Healthcare coverage	41941	0.88	0.04	0.76	0.97
Crime Rate	41941	0.03	0.01	0.00	0.08
Funded amount	41941	14928	7.1e+07	800	35000
Term	41941	3.6	0.92	3	5
Interest rate	41941	13.23	4.40	5.32	28.99
Grade	41941	2.79	1.31	17.3	7
Annual income	41941	76851	73923	4500	8.9e+06
Year	41941	2014	1.35	2008	2015
Fico score	41941	697	30.3	642	847
Debt-to-income	41941	18.1	8.28	0	136.97
Employment	41941	6.02	3.66	0	10
Population	41941	1.49e+07	1.16e+07	548400	3.83e+07

***Table 10**: Descriptive statistics for accepted loans.*