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P2P Lending Volume and Market Interest Rate

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Introduction

In the past, people who wanted to get a loan inevitably had to recur to the traditional financial institutions, namely the banking industry. Nowadays, especially thanks to the development of new and more efficient technologies, alternatives to the more conventional bank loans are emerging and consolidating: an example is peer to peer (P2P) lending, a rapidly growing industry. The distinctive and innovative mark of P2P lending is that it provides loans without recurring to any types of financial intermediaries, in a much more simple and quicker way compared to typical bank loans. Indeed, it directly matches borrowers and lenders. Potential borrowers have to compile an easy online application form. Then, the P2P lending platform will decide if they can get a loan and under what conditions. Particularly after the global financial crisis of 2008, the growth of P2P lending was significantly rapid.

Therefore, in a world where P2P lending is increasing its impact in the financial services, it can be useful to analyse how P2P loans are affected by monetary policy and market interest rates. The objective of this study is to verify how P2P credit provision, in the U.S., reacts to changes in interest rates. We investigate this issue from two perspectives: first, the individual loan size's reaction to change in market interest rates, also clustering the loans by address state and grade category; secondly, we examine the relationship between the marginal cost of funding and the credit provision, aggregating the loans at monthly level.

This work is organised in four chapters. In the first, we focus on delineating the P2P industry, explaining its recent history, growth and development, and the advantages that characterize its business model. In addition, given that the data on which this empirical analysis is built is directly acquired from Lending Club, we provide a description of this corporation, the world's largest P2P platform. In the second chapter, we describe the theoretical framework we adopt to implement the empirical estimations on the data: "*Credit Rationing in Markets with Imperfect Information*", a model developed by Stiglitz-Weiss in 1981. This explains the determinants and the conditions of credit rationing, that is the interest rates and riskiness associated to the borrowers. Then, in Chapter 3, we investigate the characteristics of the data used for the estimations and explain its relation to the manipulations and computations we perform. Hence, we delineate some explicative characteristics about Lending Club loans: volumes, interest rates, grade categories, default probabilities and risk-adjusted interest rates. We also describe the market interest rate, as 3-Month USD LIBOR, and the control variables, Unemployment, Gross Domestic Product and Consumer Price Index, that we add to the estimations to improve the results' accuracy.

The central part of this thesis is Chapter 4, where we present the results of the estimations. First, we summarize the econometric techniques that we adopt to the original dataset, a pooled cross section, and to its manipulations and aggregations, by generating two separated panels and a time series. We simply apply the generic linear regression model, estimable by Ordinary Least Squares (OLS), and we add the required options and specifications, in relation to the characteristics of the different datasets on which we work. Then, we present the empirical evidences we derive from it: first, the effect of the market interest rate on individual loan size and on credits, separately clustered by address state and grade category. Second, the influence of 3-Month USD LIBOR on the total amount of loans, aggregated at monthly level. Finally, we recap the issues discussed in this analysis, providing some conclusive interpretations about the empirical findings. Thus, we explain how the these results, due to the magnitude of Lending Club corporation, can be extended to the entire reality of the market-based lending in the U.S. Furthermore, given the growing future development and impact of P2P lending, this study reveals that policy makers will also have to care about the effects of the market interest rate on P2P credit channel.

Chapter 1

The P2P Industry

The object of this analysis is to argue how, in the US, marketplace lending[1] reacts to market interest rate, exploring in what way financial innovation may impact on the credit channel of monetary policy. Hence, to better understand these mechanisms, it is necessary to describe how the P2P industry is structured. This chapter focuses on providing a general description of the P2P industry, concentrating on P2P lending. We start by delineating its origin and diffusion, and we describe the impact of P2P technology in the world of the financial services. Then, we expose the advantages of P2P lending platforms, as opposed to the traditional financial institutions. We also explain the rapid growth and expansion of this phenomenon in the U.S., and we define its business model. Finally, in the last section of this chapter, we introduce Lending Club corporation and its platform, which data, available on the company's website, we have consulted to support this empirical analysis.

1.1 History and Origin of P2P

Peer to peer (P2P) lending platforms are increasing their impact in the world of the financial services. A report from PricewaterhouseCoopers[2] (2015) pointed out that, since 2007, the origination volumes of U.S. P2P lending platforms have grown on average of 84% per quarter. Firstly, let us define P2P lending platforms: these are market-based institutions which matches borrowers and lending directly, eliminating the relationship between financial intermediary and borrowers. In fact, the term "peer-to-peer" describes the interaction between two parties without the need for a central intermediary. The term's origin is found in the field of computer

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[1] In the U.S., the terms "marketplace lending" or "market-based lending" are often preferred to the expression peer to peer (P2P) lending.

[2] PricewaterhouseCoopers (2015), *Peer Pressure: how peer-to-peer lending platforms are transforming the consumer lending industry*. This report has been realized by PWC Consumer Finance Group, specialised in offering audit and advisory services covering the full spectrum of consumer lending asset classes.

networking, used to describe a network where any computer can act as either a client or a server to other computers on the network, excluding the necessity to connect to a centralized server. Clearly, the recent growth of P2P phenomena has also been facilitated by the rapid diffusion and development of the internet channels. The first P2P service to become widely adopted was the file sharing, where users could connect directly with other users on the network in order to share files such as photos, music, movies or games.

Regarding the birth and development of peer to peer services in finance, in the U.S. the story can be traced back to the launch of two companies: Lending Club and Prosper, both founded in 2006. As market-based lending platforms, they both facilitate peer to peer lending, allowing borrowers and lenders to bypass banks and deal directly with each other through a central marketplace. In parallel, in those years, a wide range of alternative peer to peer financial services, operating outside of conventional banking and capital markets, have emerged. These include:

- Crowdfunding: where many smaller contributions from individuals (the crowd) are raised for a specific project (the funding).
- Alternative foreign exchange platforms: where individuals and businesses exchange foreign currencies without recurring to banks or financial intermediaries.
- Non-bank invoice discounting: where small firms can improve their cash flows by securing advances from investors against invoices due.
- Cryptocurrencies: such as Bitcoin and LiteCoin, they are digital assets, characterized by the absence of a central issuer and which support instant online payments.

All these alternative forms of finance have peer to peer features that, without the need for a central coordination, allow their users to opt for the services they are looking for independently. In this part of the present work we focus on the advantages of P2P lending as opposed to traditional banks, and, through the diffusion and recent growth of this phenomenon, we investigate its business model.

1.2 The Advantages of P2P

Since the very beginning of their activity, P2P lending platforms have been characterized by a rapid growth. In recent years, they doubled their business annually. The progressive development and diffusion of the internet and the exploitation of new technologies, facilitating the disintermediation by allowing parties to communicate directly with one another, are of course fundamental reasons.

Yet the main justifications and explanations for the rapid expansion of P2P lending are found in a number of competitive advantages over the incumbent suppliers, the banks. In fact, banks are regulated institutions with balance sheet costs of credit provision, while P2P platforms do not hold any of the loans themselves. These differences originate some advantages, that can be grouped into four categories, see Mile and Parboteeah (2016):

- Thanks to relatively low fees for borrowers, P2P lending platforms can offer better rates of return than those available on bank deposits. Indeed, administrative and overhead costs required for setting up a P2P platform are relatively low, if compared to those faced by the traditional banking sector. Moreover, since the nature of P2P allows to match borrowers and lenders directly, there are no additional required margins of interest. Hence, the higher risk, at which P2P lenders are exposed, has to be compensated by much higher rates of return.
- Provision of credit to some categories of borrowers unable to access traditional bank lending. The recent 2008 global financial crisis has made banks and traditional lenders more reluctant to provide credit, imposing more stringent criteria, in particular to some categories of borrowers. Therefore, some individuals and small businesses find in P2P lending

services an alternative willing to take on the risk of providing such loans or to offer them at lower rates of interest.

- A perception that P2P lending is more responsible and of greater social value than conventional banking. This opinion, strengthened by the events of the 2008 financial crisis, is strictly related to the fact that these lending platforms directly link borrowers and lenders, without recurring to any kind of intermediary. So, market-based lending is perceived to offer a more socially beneficial form of finance, without the concerns, addressed to conventional financial intermediaries, that they exploit their market power and pursue profit without adequate regard to their own customers' interests.
- Constant technical innovation improving the quality, efficiency and speed of the service, both for borrowers and lenders. Differently, the banks, characterized by large legacy systems, spend a great deal of money in maintaining their existing systems rather than innovating them. Furthermore, the resources that the traditional banking sector could spend in R&D to develop new technologies and innovative services for customers have been considerably reduced after the 2008 global financial crisis. In fact, a report from Boston Consulting Group revealed that banks have paid about $321 billion in fines and compensations, since the 2008 financial crisis, for a series of violations and illegal actions. On the contrary, P2P platforms can exploit the latest web technologies to offer better quality and more efficient services to both lenders and borrowers, exploiting a competitive advantage with respect to traditional financial institutions.

Therefore P2P platforms, thanks to their innovative feature of directly matching borrowers and lenders, offer major competitive advantages over established banks. These aspects represent the key for the success and rapid rise of P2P lending and they make perceive that this phenomenon is not destined to stop. The same report from PricewaterhouseCoopers (2015), quoted above, also revealed that P2P lending could grow by 2025 to capture 10% of the $8000 Billion U.S.

market for revolving consumer debt and 4% of the $1.4 Trillion of non-revolving consumer debt held by U.S. financial institutions. Morgan Stanley Research[3] (2015) forecasted that P2P lending will capture 10% of U.S. lending by 2020 and reach a stock of $150-$490 Billion globally.

1.3 The Growth of P2P Lending in the U.S.

Together with the U.K., the United States have been the pioneers in the development of P2P lending. As we already said, the beginning of P2P lending in the U.S. needs to be traced back to 2006, when two of the most important market-based lending platforms, Lending Club and Prosper, were founded. U.S. P2P lending is much more focused on consumer credit and, in fact, Lending Club and Prosper, the oldest and largest American platforms, were established to offer consumer lending and refinancing of student loans. Then, other platforms came into the wide world of P2P lending, focussing on consumer lending. The most well established are Avant, specialised in personal loans, and SoFi, concentrating on the refinancing of student loans. OnDeck, CAN Capital and Kabbage are the leading providers of market place loans for small businesses. GroundFloor and LendingHome, instead, are specific for the provision of short-term bridge mortgage finance. Though many P2P lenders were established before the 2008 financial crisis, they gained strength after that. Indeed, traditional banks suffered heavy losses and the subsequent chaos and fragility in the financial system caused dissatisfaction and lack of confidence among borrowers, generating unmet demand for loans. P2P lending platforms came into this context, stepping into the vacuum that the banking and monetary system left worldwide.

P2P lending in the U.S., compared to other financial services, is growing at a faster pace. According to the federal reserve bank of Cleveland[4], the total amount of money lent through P2P platforms grew more than 80% per quarter from 2007 to

[3] The division of the investment research of the leading global financial services firm, Morgan Stanley.
[4] The Cleveland-based headquarters of U.S. Federal Reserve.

2014. Even if it is impossible to deny the growth and development of P2P lending, this still constitutes a small fraction of the U.S. unsecured consumer lending. Morgan Staley Research (2015) puts the level of marketplace lending at $12 Billion at the end of 2014, standing for only the 0.36% of total U.S consumer loans of $3.3 Trillion. Nevertheless, the expansion of P2P lending is consistent and solid, as observed by a recent report from the Cambridge Centre for Alternative Finance[5], which attested the level of the market-based lending loans at $25.7 Billion, at the end of 2015. In the U.S., P2P lending is seen not as in competition with the traditional banking sector, but as an opportunity to increase the services offered to lenders and borrowers. Market-based lending forms represent an alternative source of investment assets for banks with surplus funds and they are seen as a model for improved technology, deposit and loan customers. Due to this, many American P2P lending platforms have developed partnerships with U.S. banks.

The development of P2P lending in the U.S. is, of course, strictly related to the evolution of the laws and regulations that are applied to it. In the U.S., P2P lending platforms do not only need to be in compliance with Security and Exchange Commission[6] (SEC) regulations, but they also have to operate in unison with the respective state laws. The immediate priority of the regulators is an appropriate oversight on operational risks and customer protection. In the U.S., competent authorities are extremely concerned about the need for consumer and prudential regulation. The U.S. Consumer Financial Protection Bureau[7] (CFPB) is increasingly involved in the oversight of P2P lending. This supervision has brought to a well-publicised enforcement action against Lending Club for lack of clarity on interest rates paid by one group of borrowers. One challenging regulatory limit that market-

[5] Known as CCAF it is an academic research institute dedicated to the study of alternative finance. The centre is part of the Judge Business School, University of Cambridge.

[6] Securities and Exchange Commission is an independent agency of the U.S. federal government. It acts to protect investors, helping them to make informed decisions and to invest with confidence. Hence, it promotes fairness in the securities markets and shares information about companies and investment professionals.

[7] Consumer Financial Protection Bureau is an agency of the U.S. government responsible for consumer protection in the financial sector. It makes sure banks, lenders and other financial companies treat consumers fairly.

based platforms face, is the limitation on consumer loan interest rates applicable in many states. To deal with this aspect, U.S. marketplace lenders work with partner banks, who formally grant loans once they are agreed on the P2P lending platform before selling them back to the platform investors. Hence, U.S. regulators need to ensure an adequate oversight, but at the same time they have to act without blocking the financial innovation and the use of P2P platforms, which provide credit to borrowers who are unable to borrow from banks.

1.4 The Business Model of P2P Lending

The business model on which P2P lending platforms are built is very simple: they directly match borrowers and lenders, without recurring to any form of intermediation. Differently from banks, they do not lend their own funds, but they act as a platform to put borrowers, who are seeking a loan, onto investors, who purchase notes or securities backed by notes issued by P2P platforms. P2P lending institutions generate revenues from the fees charged to borrowers and from a portion of the interests charged to investors, as servicing fees or additional charges, as late fees. The remaining part of the interests, that borrowers pay on the loan, constitutes the revenues collected by the investors. Borrowers benefit from the loan and from a very simple and quick online application process: they have to fill out an easy online application form, wait for the approval process in a few times and then follow the status of their loan application.

The difference from the business model of conventional banking is evident. In fact, traditional banks, whose main activity is the provision of liquidity, offer a wide range of services together: deposits, lending, guarantees and securities trading. They manage a wide and well-diversified business which allows them to exploit economies of scale, lowering their cost of funding and boosting their returns. However, since the money they provide is owned by themselves, they need to carefully assess the creditworthiness of their customers. Moreover, the traditional financial institutions' business requires other skills and competencies: the knowledge needed to extend loans to particular categories of agents (screening), the constant monitoring of the behaviour of borrowers and the legal administration of the exposure following a default.

Therefore, assumed this theoretical and conceptual background and looking at the experience of P2P platforms in U.S. and U.K., it is evident that it has been much more difficult to persuade depositors, rather than borrowers, to participate on P2P platforms. Hence, market-based lending had to attract institutional investments to maintain its strong rhythm of growth. In fact, many bank customers have preferred to borrow money from P2P platforms to benefit from comparatively low interest rates or access otherwise unavailable credit. Vice versa, the main constraint is on the investor side: lending on P2P rather than making a bank deposit means losing the deposit insurance protection and dealing with unfamiliar and unconventional products. Nevertheless, P2P lending platforms provide a high level of transparency and strong track record of recent performances, to sustain the attractiveness of their alternative instruments of investment. So, the customers, both lenders and borrowers, most easily attracted by the better rates offered by P2P platforms, will be those with the least need for the liquidity services provided by the banks.

Thus, the impact of P2P lending should be viewed as complementary to, rather than competitive with bank offerings. The banking sector's reaction confirms this theory: they are setting up their own P2P platforms or cooperating with the existing ones, allowing them to market P2P borrowing to their customers and improving the availability of credit to those who do not easily qualify for conventional bank lending.

1.5 Lending Club in the P2P Lending Industry

The present study focuses on determining how the P2P industry is affected by changes in market interest rates, identifying the way in which the marginal cost of funding can influence market-based lending's loans provision. We empirically derive the relationship between the 3-Month USD LIBOR and loan volume originated through the Lending Club's platform. Indeed, Lending Club is the world's largest online marketplace connecting borrowers and investors, virtually embodying the U.S. P2P lending industry.

Lending Club was founded in 2006 and it is headquartered in San Francisco, California. As a P2P lending platform, it does not act as a traditional bank, but it connects borrowers with investors through its online marketplace. Investors, according to information about the potential borrowers' creditworthiness provided by Lending Club, offer their money in exchange for interest income. Customers interested in a loan need to complete a simple application form on the company's website. Lending Club, after having analysed the profile of these potential customers, determines grades and corresponding interest rates to be applied to qualified borrowers. Then, investors, ranging from individuals to institutions, select loans in which to invest, consistent with their risk profile, and earn, each month, part of the principal repayment and returns in form of interests. The mission the company declared in its most recent annual report[8] is to transform the banking system, to make credit more affordable and investing more rewarding. This ambitious objective is supported by the potentialities of the technology-powered marketplace: it is considered the best way to make capital more accessible to borrowers and investors.

The corporation provides services that increase the efficiency and improve the borrowers and investors experience with ease of use and accessibility, reducing the need for physical infrastructure and manual processes, differently from the traditional banking system. Lending Club provides all the typical advantages of P2P lending; it allows consumers and small businesses owners to borrow, lowering the cost of their credit and enjoying a more seamless and transparent experience than the one provided by traditional banks. On the other side, investors use Lending Club attracted by higher interest rates from an asset class that has generally been available to limited institutional investors. Through its market-based lending platform, Lending Club has made available more assets for more investors, including

[8] Lending Club annual report, 2016.

retail investors, high-net worth individuals and family offices, banks and finance companies, insurance companies, hedge funds, foundations, pension plans and universities endowments. The corporation implemented a developed technology platform to offer intuitive and efficient services and to support its marketplace. It has automated several key aspects of its operations, including the borrower's application process, data gathering, credit scoring, loan funding, investing and servicing, regulatory compliance and fraud detection. In addition, the platform offers sophisticated analytical tools and data to foster its transparency and help investors make informed decisions. Similarly to other P2P platforms, Lending Club generates revenues from transaction fees, received from both lenders and borrowers. A large proportion of its revenues are transaction fees paid by borrowers when loans are originated. It also collects servicing fees from investors, deducted from interest and loan repayments: a 1% fee is applied to investors on each payment received. However, if borrowers miss a payment, Lending Club does not require any commission until the payment amount is collected.

As it is possible to observe from Section 3.1.2, in Chapter 3, where we present some statistics and data about Lending Club loans volume, the growth of the corporation is significant and in line with the expansion of P2P lending industry. It was the first P2P lender to register its offerings as securities with the Security and Exchange Commission (SEC) and on August 27, 2014, it filed for an IPO with the SEC which took place in December 10, 2014. Despite thanks to the IPO, the company raised $900 million, and the stocks ended the first trading day up 56%, reaching its maximum at $25.74, a few days later, the post-IPO price performances, in the medium-long period, disappointed the investors. In fact, at the end of 2015, Lending Club's stocks were traded at almost $11 and they continued diminishing. At the end of 2016, shares declined to less than $6. This negative trend is related to the investor's worry about the ability of persisting in those relevant levels of growth and to the economic performances registered by the company. In the year ending 31 December 2014, Lending Club registered a substantial net loss of $32.9 million. In the 2015, the company pursued an expansionary strategy with large expenditures on sales and marketing, engineering and product development but, thanks to the relevant growth of its loans volume, and subsequent to transaction fees, it reduced the net loss to $5 million. However, the year ending with 31 December 2016 was even worst: due to sales and marketing, engineering, product development, servicing and administrative operating expenses superior to the 2015, the company registered a net loss of $145,969 million. The increment of transaction, servicing and management fees was not enough to guarantee a positive profit to the company. These financial statements highlight one concern about Lending Club and other marketplace lenders. The high levels of transaction fee revenues are an outcome of the high rates of growth of loan volume. As this kind of business matures, slowing this growth, Lending Club, but also the other marketplace lenders, will have to engage in substantial cost reductions to be profitable. Investors might doubt that Lending Club and the other P2P lenders will be able to maintain the rapid rate of growth in loans origination that also supported their strong revenues increase. Moreover, the high levels of default rates, that we show in detail in Section 3.1.4, is causing investors to have serious doubts about future growth of Lending Club and P2P lending. However, since the market share of P2P lending is relatively low if compared to the other traditional financial institutions, rapid future growth is still possible.

Chapter 2

Literature review and Theoretical Background: the Stiglitz-Weiss Model

In this chapter, we illustrate the theoretical framework adopted for the empirical analysis: "*Credit Rationing in Markets with Imperfect Information*", a model developed by Stiglitz-Weiss in 1981 which explains the determinants and the conditions of credit rationing. We start by introducing the model, explaining the role of the interest rates as screening device that determine the rationing of credit provision. Following the illustrations provided by Stiglitz and Weiss, we describe the way in which interest rates allow banks to identify typologies of borrowers, and so how they induce the financial institutions to limit loans volume. Then, we explain the role of the collateral. Stiglitz and Weiss showed that, despite the fact that the collateral may have beneficial incentive effects, it also may increase the riskiness of the borrowers, potentially reducing the banks' profits, and causing credit rationing. Finally, we propose Stiglitz-Weiss explanations of the credit rationing in relation to distinguishable typologies of borrowers, characterized by different risk profiles. Thus, we adopt the present credit rationing model to explain, from a theoretical point of view, how the borrowers' interest rates and risk profiles influence loans volume in credit market.

2.1 Structure and Framework of the Model

Our goal is to estimate the elasticity of credit provision to interest rates, investigating how the marginal cost of funding can influence Lending Club's loan volume. We approach this issue by using a linear model implemented by Stiglitz-Weiss[9], where credit provision depends on interest rates and borrowers' risk. In

[9] Joseph Eugene Stiglitz is an American economist and a professor at Columbia University. He is a recipient of the Nobel Memorial Prize in Economic Sciences (2001). Moreover, he also is the former vice president and chief economist of the World Bank. Andrew Weiss is founder and Chief Executive Officer of Weiss Asset Management, a Boston-based investment firm and he is a Professor Emeritus at Boston University.

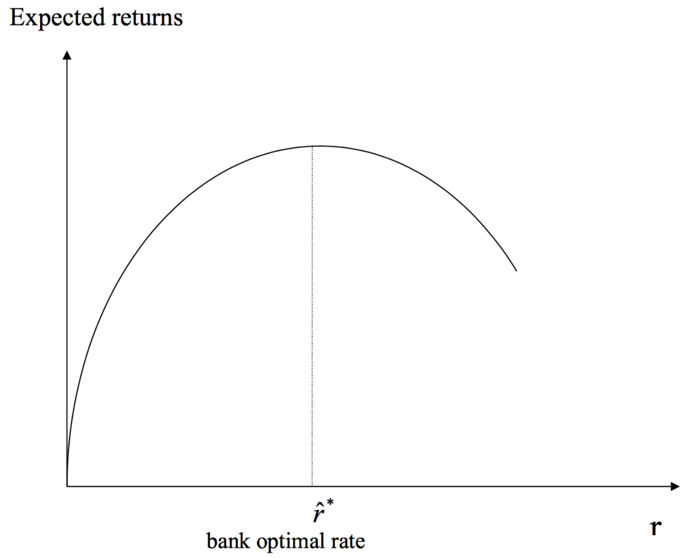
their study, Stiglitz and Weiss analysed the banking sector and its system of credit provision and they individuated the determinants and conditions of credit rationing.

If we only looked at the general theory of economics, we would immediately argue that credit rationing does not exist. It is well known that market equilibrium is reached when supply equals demand. In fact, if demand should exceed supply, prices would rise, causing the decrease in demand and/or the increase supply until demand and supply are equated at the new equilibrium price. Analogously, the opposite would happen for an excess in the supply, implying a new price of equilibrium. Thus, if prices did their job, credit rationing would not occur. However, this does not happen and credit rationing and unemployment actually exist. Stiglitz and Weiss showed that, in equilibrium, loans market can be characterized by credit rationing, and they identified its key determinants in the level of interest rates and in the borrowers' risk.

In fact, when financial institutions issue loans, they are mainly concerned about the interest rate they receive and the related riskiness that is associated with the borrowers. Since the expected return to the bank is linked to the probability of repayment, financial institutions aim to identify the borrowers' creditworthiness. Hence, to avoid the adverse selection effect and to distinguish between "Good Borrowers", who are more likely to repay, and "Bad Borrowers", banks use a variety of screening devices. The interest rate a bank charges may itself reflect the riskiness, acting as screening device: those who are willing to pay high interests may, on average, be worse risk. They accept to pay high interest rates because they perceive that their possibility of repaying the loan is quite low. Therefore, higher average interest rates can be interpreted by banks as increasing riskiness of those who borrow, consequently implying the potential decrease of banks' profits. Analogously, higher interest rates could induce economic agents to undertake riskier projects, characterized by lower probabilities of success but higher payoffs if successful. Consequently, there is not a perfect linear relationship between banks' returns and the interest rates they charge: as it is possible to observe by looking at

Figure 1, the bank's expected return may increase less rapidly than the interest rate and, beyond a point, it may decrease.

Figure 1: the Interest Rate that Maximizes the Return to the Bank.



This point, indicated as $\hat{r}^*$, represents the bank's optimal rate, the interest rate at which the expected return to the bank is maximized. Indeed, after a certain level of interest rate, the expected return to the bank starts decreasing due to the adverse selection effect and the related excessive riskiness.

Both demand for loans and supply of funds are functions of the interest rate and the latter is determined by the bank-optimal rate. Even if demand and supply are not at the same level, the equilibrium is fixed at $\hat{r}^*$, the equilibrium interest rate. So, the bank would not lend to an individual who offered to pay more than $\hat{r}^*$, because such a loan would represent a worse risk compared to the average loan at interest rate $\hat{r}^*$ and this would imply a lower expected return. Therefore, the bank is rationing credit and there are no competitive forces leading supply to equal demand. But there also is another factor which could influence loan provision and the behaviour of borrowers: the collateral. Stiglitz and Weiss proved that increasing the collateral of lenders beyond a certain point might decrease the returns to the bank.

2.2. The Interest Rate as a Screening Device

The interest rate has a primary role in determining the rationing of credit provision because it acts as screening device, helping banks and financial institutions in evaluating related risks. In their model, in order to enlighten the function of interest rate as screening device, Stiglitz and Weiss assumed that the bank, after having identified potential projects (θ), looks at the probability distribution of the gross return (R) of all these possible investments. They started from the distribution of returns:

$$F(R, \theta)$$

and the density function of the returns:

$$f(R, \theta)$$

assuming that greater θ corresponds to greater risk, in the sense of mean preserving spreads (see Rothschild-Stiglitz, 1976). For example, for $\theta_1 > \theta_2$, this can be represented as:

$$\int_0^\infty Rf(R, \theta_1)dR = \int_0^\infty Rf(R, \theta_2)dR$$

then for $y \geq 0$,

$$\int_0^y F(R, \theta_1)dR \ \geq \int_0^y Rf(R, \theta_2)dR$$

Thus, if an individual borrows an amount B, at the interest rate $\hat{r}$, he will default on his loan if the return R plus the collateral C is insufficient to pay back the promised amount[10], that is if:

$$C + R \leq B(1 + \hat{r})$$

Therefore, the return to the borrower, $\pi(R, \hat{r})$ can be written as:

$$\pi(R, \hat{r}) = \max\,(R - (1 + \hat{r})B; -C)$$

whereas the return to the bank can be scripted as:

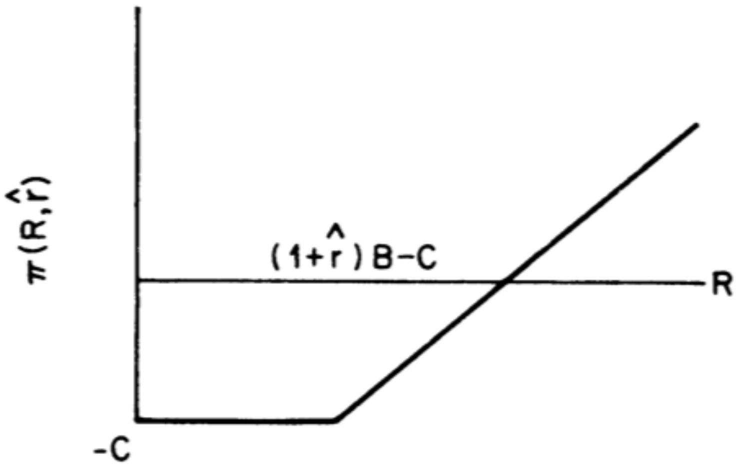
$$\rho(R, \hat{r}) = \min\,(R + C; B(1 + \hat{r}))$$

This means that the borrower must pay back either the promised amount or the maximum he can pay back (R+C).

Before mathematically illustrating how the interest rate acts as screening device, it is necessary to clarify the assumptions on which this reasoning is built: the borrower has a given amount of equity; borrower and lender are risk neutral; the supply of loanable funds available to a bank is unaffected by the interest rate it charges borrowers; the cost of project is fixed and potential projects are not divisible. Stiglitz and Weiss showed that for a given interest rate $\hat{r}$, there is a critical value $\hat{\theta}$ such that a firm borrows from the bank if and only if $\theta > \hat{\theta}$. This can be evinced by looking at Figure 2, representing the net return to the borrower: profits are a convex function of R.

10 Assuming that, if the firm defaults, the bank has first claim on R+C, and ignoring bankruptcy costs.

Figure 2: Return to the Borrower as a Convex Function of the Return on the Project.



In addition, Stiglitz and Weiss also showed that an increase in the interest rate applied by banks determines a growth of the critical value of θ, below which individuals do not apply for loans. This is deduced by differentiating the following equation, representing the value of $\hat{\theta}$ for which expected profits to the bank are zero:

$$\pi(\hat{r}, \hat{\theta}) \equiv \int_0^{\infty} \max\,[R - (\hat{r} + 1)\,B; -C]\; dF(R, \hat{\theta}) = 0$$

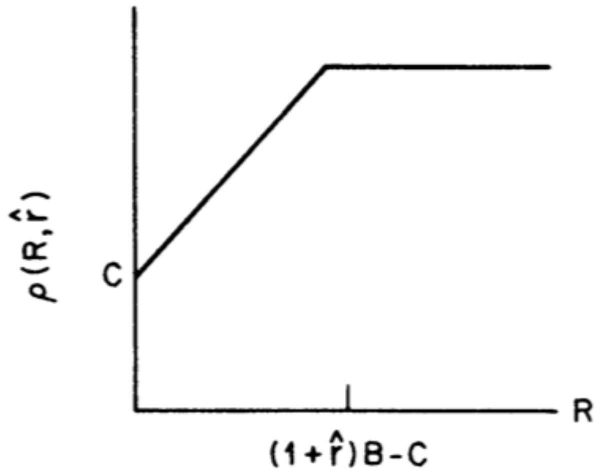
Hence, differentiating it:

$$\frac{d\hat{\theta}}{d\hat{r}} = \frac{B \int_{(1+\hat{r})B-C}^{\infty} dF(R, \hat{\theta})}{\frac{\partial \Pi}{\partial \hat{\theta}}} > 0$$

for each θ, expected profits are decreased.

Stiglitz and Weiss demonstrated that the expected return on a loan to a bank is a decreasing function of the riskiness of the loan. This is immediately proved by looking at, $\rho(R, \hat{r})$, the equation expressing the return to the bank. In fact, as it is possible to observe through Figure 3, the return to the bank is a concave function of the return on the project.

Figure 3: Return to the Bank as a Concave Function of the Return on the Project.



The authors of the model also analysed the effects of an increment in $\hat{r}$. They demonstrated that an increase of the interest rate $\hat{r}$ would not only have the direct effect of increasing the return to the bank, but it would also determine an indirect adverse-selection effect, acting in the opposite direction. In these circumstances, $\bar{\rho}(\hat{r})$, mean return to the bank from the set of applicants at interest rate $\hat{r}$ will not be a monotonic function of $\hat{r}$, since at each successive group drops out of the market, there will be a discrete fall in $\bar{\rho}$. This proof can be explained more simply with an example. Let us assume there are two groups: the "safe" one, borrowing at the interest rate r_1, and the "risky" one, borrowing at r_2, clearly with $r_1 < r_2$. If the interest rate is raised above r_1, the mix of applicants changes dramatically since all low risk applicants withdraw.

2.3 The Interest Rate as an Incentive Mechanism

Stiglitz and Weiss provided another incentive for banks to ration credit: the increase of the interest rate applied by banks could induce lenders to prefer riskier projects, for which the return to the bank might be lower. Actually, lender and borrower have different priorities: the former is interested in receiving back the capital and the interests' repayments and so is concerned with the actions of the borrower only to the extent that they affect the probability of bankruptcy; the latter is instead mainly focussed on the return he could make on the investment. Since it is very difficult for the lenders to constantly and perfectly monitor the borrowers' behaviour, banks also have to take into account the effect of the interest rate on the behaviour of the borrowers. Indeed, raising the rate of interest could induce borrowers to take actions against the lenders' interests, potentially decreasing the banks' profits.

Stiglitz and Weiss showed how this difference of priorities may induce banks to ration credit. First, they assumed that each firm has a choice of projects, denoted by superscripts *j* and *k*. Thus, if at a given nominal interest rate *r* a risk neutral firm is indifferent between two projects, and if banks decided to increase the interest rate, the firm would prefer the project with the higher probability of bankruptcy, but at the same time also the higher expected return. This consideration has been proved starting from the expected return to the i^{th}project, having the following form:

$$\pi^i = \mathrm{E}[\max\left(R^i - (1+\hat{r})B, -C\right)]$$

so, deriving respect to $\hat{r}$:

$$\frac{d\pi^i}{d\hat{r}} = -B(1 - F_i\left((1+\hat{r})B - C\right))$$

Therefore, if at some $\hat{r}$, $\pi^j = \pi^k$, the increase in $\hat{r}$ lowers more the expected return to the borrower from the project with the higher probability of paying back the loan than the decrease of the expected return characterizing the project with the lower probability of repaying back the loan. On the other hand, we previously demonstrated that the bank prefers to lend to the safer projects since they clearly have the lower probability of default. Hence, raising the interest rate could imply negative consequences for the bank, since riskiness of loans could increase, lowering the expected return to the bank.

2.4 The Theory of Collateral and Limited Liability

Stiglitz and Weiss also demonstrated the reasons why banks will not increase collateral requirements as a means of allocating credit. Increasing collateral would not directly imply a reduction of losses to the bank, in case of default, and so it does not always mean increasing the return to the bank. Considering that wealthier individuals are likely to be less risk-averse, it is reasonable to think that those who could put up the most capital, as a form of collateral, would also be willing to take the greatest risks. Under plausible conditions, the increase of the riskiness of the projects that borrowers could undertake is a sufficient condition to lower the bank's return. In their explications, Stiglitz and Weiss assumed that all borrowers were risk-averse, with the same utility function $U(W), U' > 0, U'' < 0$. However, they supposed that individuals were different with respect to their initial wealth, W_0. Each borrower has a set of projects to undertake, each one with a probability of success $p(R)$, where R is the return if successful; otherwise, if unsuccessful, it is zero. This implies that $p'(R) < 0$. In addition, everyone also has an alternative safe investment opportunity, yielding the return ρ^*.

Since the bank cannot directly observe either the individual's wealth, or the project undertaken, it offers all borrowers the same contract, characterized by C, the amount of collateral, and $\hat{r}$, the interest rate. So, the contract, described by two elements $\{C, \hat{r}\}$, operates as a screening device in relation to the borrowers' wealth. In fact, supposing that there exist two critical values of W_0, that is $\widehat{W}_0$ and $\widetilde{W}_0$, if there is decreasing absolute risk aversion, all individuals with wealth $\widehat{W}_0 < W_0 < \widetilde{W}_0$ apply for loans. Moreover, if there is absolute risk aversion, wealthier individuals undertake riskier projects. Stiglitz and Weiss derived this assertion showing:

$$\frac{dR}{dW_0} > 0$$

Although in their model the authors found out that increasing the collateral can increase the return to the bank, since:

$$\frac{dp}{dC} > 0$$

However, it is also necessary to regard the adverse selection effect from increasing the collateral requirement, which could instead damage the banks' profits. In fact, both the average and the marginal borrower who borrows is riskier[11],

$$\frac{d\widehat{W}_0}{dC} > 0$$

Therefore, Stiglitz and Weiss proved that although the collateral may have beneficial incentive effects, it may also imply countervailing adverse selection effects. This evidence is connected to the limited control that the bank may have over the borrowers' actions. Hence, the borrower's response to the increase in lending could be to take actions which, in certain circumstances, will require the bank to lend more in the future.

2.5 Observationally Distinguishable Borrowers

Stiglitz and Weiss implemented their study abandoning the hypothesis of identity among all borrowers. They extended their analysis to the case where there are n observationally distinguishable groups, each with an interior bank optimal interest rate denoted by r_i^*. The gross return to the bank is denoted by the function $\rho_i(r_i)$, where subscript *i* means that the bank is charging its optimal interest denoted by r_i to type *i* borrower. Therefore, if we order the groups of potential borrowers so that $i > j$, this implies $max\ \rho_i(\hat{r}_i) > max\ \rho_j(\hat{r}_j)$. Thus, for $i > j$, type *j* borrowers will only receive loans if credit is not rationed to type *i* borrowers. This is very intuitive to prove: in fact, since the maximum return that the bank can earn from *j* is less than the one from *i*, the bank could clearly increase its return by preferring a loan to *i* as opposed to a loan to *j*, which would produce a lower gross profit. Consequently, the

[11] At a sufficiently high collateral, the wealthy individual will not borrow at all.

equilibrium interest rates are such that for all *i*, *j* receiving loans, functions of gross return to the bank are equal:

$$\rho_i(\hat{r}_i) = \rho_j(\hat{r}_j)$$

Stiglitz and Weiss proved this statement by contradiction: if $\rho_i(\hat{r}_i) > \rho_j(\hat{r}_j)$, then a bank lending to type *j* borrowers would prefer to bid type *i* borrowers away from other banks. Hence, if we denote with ρ^* the equilibrium return to the banks per Dollar loaned, which is equal to the cost of loanable funds if banks compete freely for borrowers, then for all *i*, *j* receiving loans:

$$\rho_i(r_i) = \rho_j(r_j) = \rho^*$$

Thus, this model of credit rationing explains how, among observationally identical borrowers too, some receive loans and others do not. Potential borrowers, whose loans have been denied, would not be able to borrow, even if they were available to pay an interest rate higher than the one established by the market. In fact, increasing the interest rate could damage the bank, consequently increasing the riskiness of bank's loan portfolio and discouraging safer investors. In addition, higher interest rates could induce borrowers to invest in riskier projects, raising the possibility of default. In this way, the bank's profits could be damaged. Credit rationing operates under these circumstances, characterized by excess of demand and no competitive forces leading supply to equal demand: it acts limiting the number of loans the bank will make, limiting the size of each loan or making the interest rate charged by the lender an increasing function of the magnitude of the loan. Consequently, banks practice credit rationing. Two main determinants are the probability of default for any borrower and the interest rate that is applied. The existence of credit rationing leads us to consider the Law of Supply and Demand not as a law, but actually as an assumption needed for competitive analysis. So, in the circumstances of credit provision we just described, that is the usual results of economic theorizing, that prices clear markets, is model specific and is not a general property of markets: it has been showed that credit rationing exists.

Chapter 3

Data Description and Data Manipulations

In this analysis, we elaborate a large amount of data. Hence, to contextualize and better understand the purpose of the study, it is necessary to explain and describe the characteristics of the datasets we use and manipulate. The data, on which the examination is based, is the following:

- Lending Club loans, for data on P2P lending.
- 3-Month USD Libor, as market interest rate representing the marginal cost of funding.
- Unemployment, Gross Domestic Product and Consumer Price Index, as control variables to improve the accuracy of the regression estimates.

In the first section of this chapter, we focus on describing the data about Lending Club loans, collected from the company's website. In relation to the period on which this study is performed, from January 2010 to December 2016, we provide some functional statistics about loan volume, interest rates, grades, loans status and address state. We also show how we calculate the default probability, used to derive the adjusted interest rate and, later, in the next chapter, to perform the estimations. Then, we describe the 3-Month USD LIBOR, which we adopt as market interest rate, representing the marginal cost of funding. Finally, we briefly delineate the control variables adopted to improve the estimations model: Unemployment, Gross Domestic Product and Consumer Price Index.

3.1 Lending Club Data

The empirical analysis is based on data about loan volume issued through the Lending Club platform. As we already explained in Section 1.5, Lending Club is a peer to peer lending company operating in the United States. As an online lending platform, it provides money to consumers or businesses through online services, matching lenders with borrowers directly and collecting fees from both borrowers and investors. In its website, the company shares a great amount of information, including the datasets about all the loans issued through its P2P platform. Each issued loan is characterized by several explicative variables, including those describing the borrowers, to provide potential lenders with as much information as possible to support them in their investment decision.

Lending Club is the world's largest P2P lending platform and for this reason we could consider it representative of the American marketplace lending. It allows borrowers to create unsecured personal loans ranging from $1,000 up to $40,000 with a 36 or 60 month maturity. According to its website, from the day the company begun its business until the end of 2016, the total volume of credit offered was $19,482,988,375. The company freely provides the datasets containing several information about consumer loans issued from 2007, until the present day. Datasets of business loans are not available.

3.1.1 Classification Dataset

In this analysis, we consider the data shared by Lending Club about consumer loans, for the period ranging from January 2010 to December 2016. We omit the data for the period 2007-2009, due to its proximity to the recent 2008 financial crisis, which clearly influenced all channels of credit provision. Lending Club provides huge datasets containing several explicative pieces of information about all issued loans. The company also gives a data dictionary file which specifies the meaning of the involved variables. All data can be freely accessed from company's website, where two types of dataset are available:

- Loan Data: these files contain complete loan data for all loans issued through the period stated, including various and latest information about the loan status, the payment and the borrower.

- Declined Loan Data: these files, instead, contain the list and details of all loan applicants that did not meet Lending Club's credit underwriting policy.

The dataset on which we work consists of 8 loan data files which we aggregate to include only those loans issued from January 2010 to December 2016. In this way, we obtain a pooled cross section. These files are updated every four months, on the same day as the quarterly results of the company are released. This means that it is possible to access to the latest payment evidences. Information about almost all issued loans is available through the dataset we collected, except for those few loans for which Lending Club was not authorized to publicly release the transactions' details. In Appendix A, we summarize the meaning of the 109 variables effectively included in the dataset downloaded from Lending Club website. We do not find a complete correspondence between the variables explained in the data dictionary (128) and those effectively present in the datasets provided by Lending Club (109). In fact, in order to download the full version of the files, it is necessary to create a Lending Club account and register as potential investor or borrower.

We start composing the dataset, a pooled cross section dataset, combining the 8 data files downloaded from the company's website, providing information about the loans issued during the period of interest. Then, we analyse the dataset year by year, and then the total amount of data for the overall period. We focus on the most relevant and significant information variables, useful to implement and improve the analysis, and monitor their behaviour in time.

3.1.2 Volume and Interest Rate

We proceed with the analysis by investigating and summarizing some descriptive statistics about interest rates and loans amount, in relation to two different available maturities. The variables we consider in this descriptive part, as scripted in the dataset, are:

- *term*: it expresses the loan's maturity, which can be 36 or 60 months. It also indicates the number of payments on the loan.
- *loan_amnt*: it is the listed amount of the loan applied for by the borrower. Since we are working with consumer loans, the amount of money a borrower can obtain ranges from $1,000 to $40,000.
- *int_rate*: it is the interest rate applied on the loan. It is calculated daily, based on a 360-day year with 12 months, each composed of 30 days, regardless if a month has more or less than 30 days. Lending Club provides each potential borrower with a credit grade and consequently an interest rate to every approved loan. Interest rates upsurge for each loan grade and sub-grade increment.

Hence, in the remainder of this section we propose an examination of Lending Club's loan volume and interest rates year by year:

- 2010 Loans Data: the number of loans provided thanks to Lending Club's platform was 12,537, corresponding to a total amount of $131,992,544. These loans are divided by maturity as shown in Table 1:

Table 1: Loans Number and Amount by Term (2010).

Term	Number of Loans	Loans Amount
36 Months	9,156	$89,740,896
60 Months	3,381	$42,251,648

Most loans have a 36 month maturity: 73% in terms of number of loans and 68% as total amount. The average interest rate applied during this period was 11.99%. The information about this variable for year 2010 is summarized in Table 2:

Table 2: Interest Rate Summarization, 2010.

Interest Rate	
Mean	11.99%
Std. Dev.	0.0349
Min.	5.42%
25^{th} pcl.	9.62%
50^{th} pcl.	11.86%
75^{th} pcl	14.59%
Max.	21.64%
Number of observations	12537

- 2011 Loans Data: the number of loans issued thanks to Lending Club increased to 21,721 (+73.26% compared to the previous year.) The total amount of loans was $261,600,000 (+98.19%), divided as follows in Table 3:

Table 3: Loans Number and Amount by Term (2011).

Term	Number of Loans	Loans Amount
36 Months	14,101	$132,800,000
60 Months	7,620	$128,800,000

Loans with a 36 month maturity represent the majority: 65% of the total and 51% as Dollar amount. During this year, the average interest rate was 12.22%, quite a similar result to the one of 2010. Its main characteristics are represented in Table 4, below:

Table 4: Interest Rate Summarization, 2011.

Interest Rate	
Mean	12.22%
Std. Dev.	0.0415
Min.	5.42%
25th pcl.	8.9%
50th pcl.	11.99%
75th pcl	15.27%
Max.	24.11%
Number of observations	21,721

- 2012 Loans Data: the number of loans issued increased significantly, reaching 53,367 (+145.69%). The total amount of loans, divided by maturity as follows in Table 5, was $718,400,000 (+174.62%):

Table 5: Loans Number and Amount by Term (2012).

Term	Number of Loans	Loans Amount
36 Months	43,470	$507,800,000
60 Months	9,897	$210,600,000

The predominance of loans with a 36 month maturity is confirmed: they constitute, respectively, 81% of the total number of loans and 71% of the Dollar amount. The average interest rate for this period, 13.64%, is greater than the one applied in 2011 and it is summarized, as follows, in Table 6:

Table 6: Interest Rate Summarization, 2012.

Interest Rate	
Mean	13.64%
Std. Dev.	0.0437
Min.	6%
25th pcl.	10.16%
50th pcl.	13.67%
75th pcl	16.29%
Max.	24.89%
Number of observations	53,367

- 2013 Loans Data: the progressive growth and diffusion of Lending Club continued in 2013: the number of loans provided by the P2P platform increased to 134,814 (+152.62%). In addition, for the first time, the total amount of loans overpassed $1 Billion: $1,982,700,000, pointing out an increase of 176% compared to the previous year. They are divided by maturity as reported in Table 7:

Table 7: Loans Number and Amount by Term (2013).

Term	Number of Loans	Loans Amount
36 Months	100,422	$1,272,000,000
60 Months	34,392	$710,700,000

A 36 month maturity months kept on being the preferred one: they enclose, respectively, 74% of the total number of loans and 64% of the Dollar amount. The average interest rate paid by borrowers is 14.53%. Its information is summarized in Table 8:

Table 8: Interest Rate Summarization, 2013.

Interest Rate	
Mean	14.53%
Std. Dev.	0.0443
Min.	6%
25th pcl.	11.14%
50th pcl.	14.33%
75th pcl	17.56%
Max.	26.06%
Number of observations	134,814

- 2014 Loans Data: the expansion of Lending Club did not stop. The number of loans was 235,629 (+74.78%), while the total amount of loans issued overpassed $3 Billions: $3,504,000,000 (+76.72%). Loans divided by maturity are exposed in the Table 9:

Table 9: Loans Number and Amount by Term (2014).

Term	Number of Loans	Loans Amount
36 Months	162,570	$2,046,000,000
60 Months	73,059	$1,458,000,000

As usual, a 36 month maturity prevails: 69% and 58% in relation to the total number and amount of issued loans. The average interest rate applied was 13.77%, for the first time lower than the previous year's one. Its information is summarised in Table 10:

Table 10: Interest Rate Summarization, 2014.

Interest Rate	
Mean	13.77%
Std. Dev.	0.0433
Min.	6%
25th pcl.	10.99%
50th pcl.	13.65%
75th pcl	16.29%
Max.	26.06%
Number of observations	235,629

- 2015 Loans Data: Lending Club's growth did not stop in 2015 either. The number of loans provided attested to 421,095 (+78.71%), corresponding to an overall amount of $6,417,000,000 (+83.13%). The division of loans by maturity, reported in Table 11, is the following:

Table 11: Loans Number and Amount by Term (2015).

Term	Number of Loans	Loans Amount
36 Months	283,173	$3,626,000,000
60 Months	137,922	$2,791,000,000

Again, most issued loans have a 36 month maturity: 67% in terms of numbers and 56% in terms of Dollars. As in 2014, the average interest rate decreased, passing to 12.6%. This is summarized in Table 12:

Table 12: Interest Rate Summarization, 2015.

Interest Rate	
Mean	12.6%
Std. Dev.	0.0432
Min.	5.32%
25th pcl.	9.17%
50th pcl.	12.29%
75th pcl	15.59%
Max.	28.99%
Number of observations	421,095

- 2016 Loans Data: the number of loans, during the last year object of this analysis, was 434,407. The percentage increment, compared to the previous year, was the lowest ever registered so far: +3.16%. In terms of amount of Dollar, the quantity remained unaltered around $6.4 billions. In addition, loans, divided by maturity, are represented in Table 13:

Table 13: Loans Number and Amount by Term (2016).

Term	Number of Loans	Loans Amount
36 Months	323,495	$4,130,000,000
60 Months	110,912	$2,270,000,000

Loans with a 36 month maturity were the majority: 74% and 64%, respectively in terms of number of loans and Dollars amount. Differently from the previous two years, the average rate of interest, which information is summarized in Table 14, increased to 13.04%.

Table 14: Interest Rate Summarization, 2016.

Interest Rate	
Mean	13.04%
Std. Dev.	0.0493
Min.	5.32%
25th pcl.	9.49%
50th pcl.	11.99%
75th pcl	15.59%
Max.	30.99%
Number of observations	434,407

- 2010-2016 Loans Data: given that the period addressed in this analysis ranges from Jan 2010 to Dec 2016, we are now going to examine the loan provision offered by Lending Club for the entire time span. The number of loans provided exceeds 1 Million: 1,313,570. As it is possible to infer from Table 15, loans with a 36 month maturity represent the majority, 71.28% of the total, while those having the longer maturity, 60 months, are 28.72%. In terms of amount of money, during these seven years, Lending Club mediated the issue of $19,422,000,000: 60.8% having a 36 month maturity and the reaming 39.2% with a 60 month maturity.

Table 15: Loans Number and Amount by Term (2010-2016).

Term	Number of Loans	Loans Amount
36 Months	936,387	$11,810,000,000
60 Months	377,183	$7,612,000,000

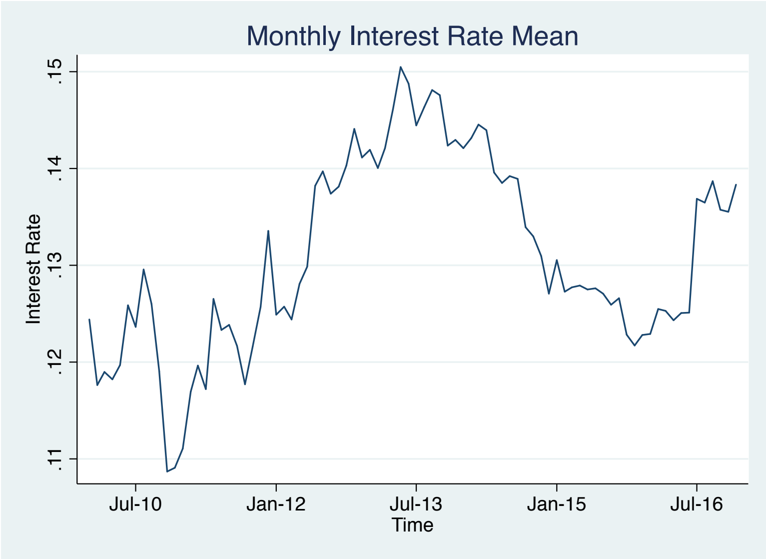
The average interest rate applied during this period, ranging from 5.32% to 30.99%, was 13.19%. Information about percentiles, minimum, maximum and standard deviation are summarized in Table 16:

Table 16: Interest Rate Summarization, (2010-2016).

Interest Rate	
Mean	13.19%
Std. Dev.	0.0458
Min.	5.32%
25th pcl.	9.75%
50th pcl.	12.79%
75th pcl	15.88%
Max.	30.99%
Number of observations	1,313,570

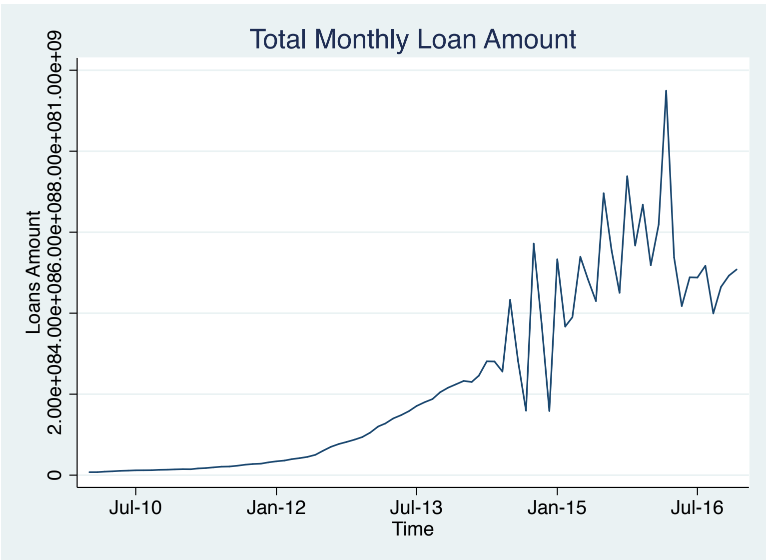
Moreover, since datasets provided by Lending Club give information on the loan's issue date not only year by year, but also month by month, we produce two time series plots: one capturing the average interest rate's evolution, the other displaying the total amount of loans provided. Thus, we compute the monthly mean of the interest rate and determine the total amount of loans issued for each month to observe the two variables' evolution in time, during the period of interest. The graph reproduced in Figure 4, reveals that the monthly interest rate, on average, reached maximum values in May 2013, while lowest values concentrated at the end of 2010. This time series highlights the absence of stationarity and of a well-defined trend.

Figure 4: Trend of The Mean of the Interest Rate, at Monthly Level.



The graph displayed in Figure 5, instead, shows how credit provision granted by Lending Club evolves month by month. The total amount of loans issued by the company increased rapidly starting from the end of 2012. The month which registered the higher amount of issued loans was March-16. The graph also confirms the tendency of U.S. P2P lending development, characterized by annually doubling the business in terms of issued loans amount, with the exception of the last year, in which the lowest increment (+3.16%) was registered.

Figure 5: Loans Volume Aggregated at Monthly Level.



3.1.3 Grades and Loan Status

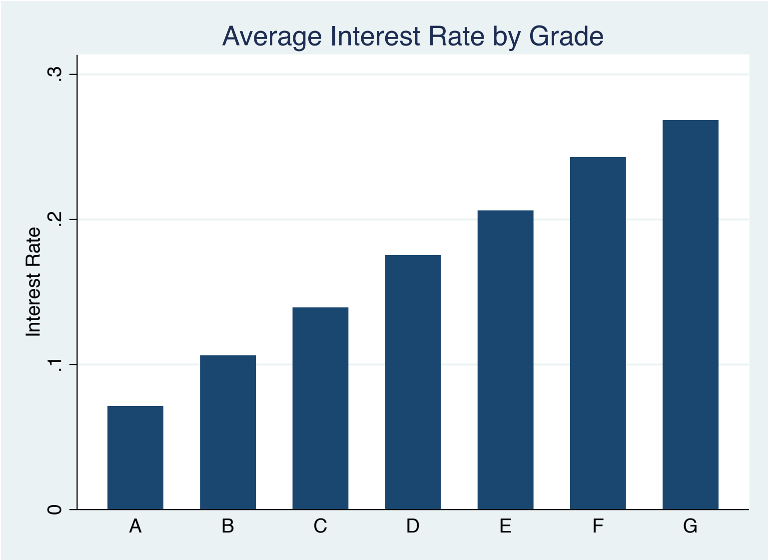
We continue describing the loans Lending Club issued during the period of interest, but here we focus on the grades the company assigned to borrowers. In Table 17, we summarize the issued loans divided by grade, computing number of loans, total amount of Dollars and average interest rate:

Table 17: Loans Statistics by grade (2010-2016).

Grade	Number of Loans	Total Amount ($)	Average Interest Rate
A	217,455	3,083,000,000	7.12%
B	386,928	5,254,000,000	10.62%
C	375,990	5,479,000,000	13.92%
D	197,397	3,094,000,000	17.52%
E	95,821	1,729,000,000	20.61%
F	32,115	617,200,000	24.29%
G	7,864	160,400,000	26.83%

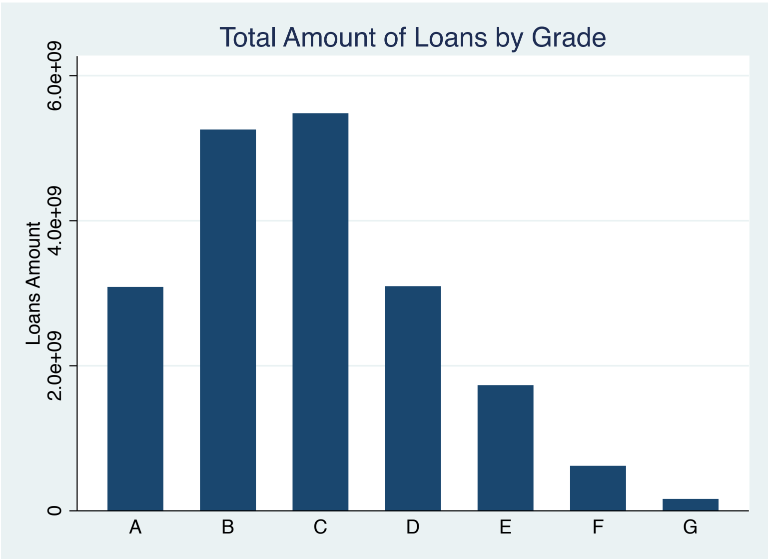
To better understand and compare how the average interest rate and the total amount of loans issued change in relation to the grades, we also create two bar charts. The first one, represented in Figure 6, compares the average interest rate applied, grade by grade.

Figure 6: Bar Chart of the Average Interest Rate Applied to the Different Grade Categories.



Obviously, the average interest rate increases when passing from loans with grade A to loans with grade G, ranging from 7.12% to 26.83%. This upside trend should reflect the incremental risk that is entangled by borrowers having higher grades, and thus default probability. The second one, Figure 7, shows the issued loans' distribution, in terms of amount of Dollar, in relation to different grades of borrowers.

Figure 7: Bar Chart of the Loans Volume Divided by Grade Categories.



It appears that most issued loans have grades B and C. They jointly represent the 55% of the total amount of issued loans from 2010 to 2016. On the contrary, loans having the higher default probability, grades D, E, F and G, are provided with minor impact compared to Dollar amount.

3.1.4 Estimation of the Default Probability of Lending Club Loans

In order to obtain a loan, Lending Club requires borrowers to complete an online application to verify if they respect some stringent credit criteria. Thus, the corporation evaluates the credit risk of borrowers, associating a grade and a sub-grade to each one of them. It determines the creditworthiness of borrowers by using an algorithm which analyses a variety of inputs: borrower credit reports, loan applications and behavioural data. In addition, the model also incorporates the historical performance of the billions of Dollars in loans facilitated through Lending Club's marketplace. Hence, according to the grade and sub-grade that are dispensed to each borrower, Lending Club assigns a corresponding interest rate to each approved loan.

Each borrower, depending on its grade, has a related default probability that is not directly specified by Lending Club. However, the dataset we downloaded contains useful information about the status of each loan, which can help us in the estimation of the default probability. Hence, in this section, we describe how we compute the default probability that can be associated to each loan, in relation to the corresponding term, 36 or 60 months, and grade, ranging from A to G. The variables from the dataset, that we use for these calculations, as scripted, are the following:

- *grade*: creditworthiness that Lending Club assigns to each borrower, according to specific criteria.
- *loan_status*: the loan's current status.
- *term*: the maturity of the loan, 36 or 60 months.

The qualitative variable *loan_status* plays a key role in the determination of the default probability. It can have the following characterizations:

- *Current*: the loan is up to date on all outstanding payments
- *In Grace Period*: the loan is past due but within 15-ady grace period
- *Late (16-30)*: the loan has not been current for 16 to 30 days
- *Late (31-120)*: the loan has not been current for 31 to 120 days
- *Fully Paid*: the loan has been fully repaid, either at the expiration of the 3- or 5-yearterm or as the result of a prepayment
- *Default*: the loan has not been current for 121 days or more
- *Charged Off*: the loan for which there is no longer a reasonable expectation of further payments. Generally, *Charged Off* occurs no later than 30 days after the default status is reached.
- *Does not meet credit policy. Status: Fully paid*: loans funded by investors and issued by Lending Club but not qualified for listing on that day. Even so, at maturity they have been fully paid.
- *Does not meet credit policy. Status: Charged off*: loans funded by investors and issued by Lending Club but not qualified for listing on that day. In this case, at maturity they have not been repaid and so they have been charged off.

In Appendices B to G, we tabulate the variable *loan status*, in relation to the period ranging from January 2010 to December 2016, clustering the loans by grade category and maturity. It can be helpful to understand in what percentage the loans we analyse in this study correspond the current, fully paid or charged off status.

To estimate the default probability, we apply a similar procedure to the one adopted by Lending Club to compute the loss rate for the determination of the

Adjusted Net Annualized Return[12]. Lending Club makes a deduction to Net Annualized Return for estimated future losses on loans, based on their status. The future losses rate is determined considering the historical charge off rate by loan status over a nine-month period. Thus, using a similar procedure, we approximate the default probability associated to each grade with the corresponding percentage of charged off loans. However, we do not consider the percentages of charged off loans registered for the whole period, January 2010 - December 2016, since we would obtain a biased estimation. Indeed, part of those loans is still current and therefore we cannot know if they will be repaid or if they will be effectively charged off. Thus, we divide the overall pooled cross section not only by grade and term but also by year. We compute for each year, grade and maturity the percentage of charged off, current and fully paid loans. Then, we approximate the default probability with the mean of charged off rate, calculated among the different years. It is important to underline that we calculate the mean including only the charged off rates of the years for which there are no more loans in status current. In this way, we can be sure that the default probability we estimate is not negatively influenced by loans still in status current. Hence, default probability for loans with a 36 month maturity is approximated with the mean of charged off rates registered in years from 2010 to 2013; instead, for loans with a 60 month maturity, the corresponding probability of default is computed as the mean of charged off rates recorded in 2010 and 2011. Thus, for all grades we compute the corresponding default probability (π), by using the following simple formulas:

$$\pi_{36\ Months} = \frac{\sum_{t=2010}^{2013} Charged\ Off\ Rate_t}{4}$$

$$\pi_{60\ Months} = \frac{\sum_{t=2010}^{2011} Charged\ Off\ Rate_t}{2}$$

[12] In its website, Lending Club monthly updates the Adjusted NAR: for each class of grade, including all loans that were issued 18 months or more before the last day of the most recently completed quarter, a corresponding net return, adjusted for potential future losses, is estimated. Adjusted NAR is a cumulative, annualized measure of the return on all the money invested in loans over the life of those loans, modelled according to the impact of potential losses associated to each grade.

In the subsequent tables we report, for each grade, year and maturity[13], the percentage of loans in status charged off[14], current and fully paid[15] and we apply the required computations to estimate the default probability:

- Default Probability: Grade A

Table 18: Loans Status by Year and Term (Grade A).

Issue Date	Term: 36 Months			Term: 60 Months		
	Charged Off Rate	**Current Rate**	**Fully Paid Rate**	**Charged Off Rate**	**Current Rate**	**Fully Paid Rate**
2010	4.36%	0	95.64%	8.37%	0	91.63%
2011	6.40%	0	93.60%	8.57%	0	91.43%
2012	7.24%	0	92.76%	6.08%	25.68%	66.89%
2013	4.54%	0	95.43%	7.23%	38.10%	53.38%
2014	4.39%	35.06%	59.64%	2.58%	69.94%	26.19%
2015	2.22%	69.88%	26.77%	1.59%	80.27%	17.26%
2016	0.57%	88.51%	10.06%	0.60%	90.14%	8.16%

Applying the formulas explained above, we estimate the default probability, obtaining the following results:

a) $\pi_{36\ Months}$ = 5.64%
b) $\pi_{60\ Months}$ = 8.47%

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[13] Notice that, in some cases, it is possible that the different loan status, charged off, current and fully paid rate, do not sum up to 100%. This happens because there are small percentages of loans in *Late (16-30 days), Late (31-120 days) or In Grace Period.* In these tables, we did not consider these values because of their irrelevance in our objective of estimating the default probability.
[14] *Charged off Rate* also includes loans that *Does not meet credit policy* but at maturity have been *charged off*.
[15] *Fully Paid Rate* also incorporates loans in status *Does not meet credit policy* but that at maturity have been totally repaid.

- Default Probability: Grade B

Table 19: Loans Status by Year and Term (Grade B).

Issue Date	Term: 36 Months			Term: 60 Months		
	Charged Off	**Current**	**Fully Paid**	**Charged Off**	**Current**	**Fully Paid**
2010	9.62%	0	90.38%	18.25%	0	81.75%
2011	10.57%	0	89.43%	15.90%	0	84.10%
2012	12.57%	0	87.43%	16.22%	18.04%	64.86%
2013	9.78%	0	90.20%	11.49%	38.52%	48.57%
2014	9.10%	30.29%	58.97%	6.96%	59.28%	31.92%
2015	5.14%	65.42%	26.94%	4.09%	76.97%	17.16%
2016	1.07%	87.21%	9.65%	0.77%	90.52%	7.11%

Again, applying the same procedure used above, we get:

a) $\pi_{36\ Months}$ = 10.64%
b) $\pi_{60\ Months}$ = 17.08%

- Default Probability: Grade C

Table 20: Loans Status by Year and Term (Grade C).

Issue Date	Term: 36 Months			Term: 60 Months		
	Charged Off	**Current**	**Fully Paid**	**Charged Off**	**Current**	**Fully Paid**
2010	13.52%	0	86.48%	21.09%	0	78.91%
2011	15.52%	0	84.48%	21.91%	0	78.09%
2012	17.57%	0	82.43%	21.34%	17.84%	59.60%
2013	15.29%	0	84.70%	17.64%	35.18%	45.36%
2014	14.90%	28.61%	54.18%	12.97%	51.35%	33.10%
2015	9.94%	58.21%	27.90%	7.27%	71.54%	17.76%
2016	2.21%	83.88%	10.50%	1.53%	87.79%	8.14%

The estimated default probabilities, for those loans identified with grade C, are the following:

a) $\pi_{36\ Months}$ = 15.48%
b) $\pi_{60\ Months}$ = 21.5%

- Default Probability: Grade D

Table 21: Loans Status by Year and Term (Grade D).

Issue Date	Term: 36 Months			Term: 60 Months		
	Charged Off	Current	Fully Paid	Charged Off	Current	Fully Paid
2010	18.60%	0	81.40%	25.31%	0	74.69%
2011	18.08%	0	81.92%	27.17%	0	72.83%
2012	21.15%	0	78.85%	27.52%	16.33%	54.77%
2013	20.37%	0	79.59%	22.38%	31.22%	44.08%
2014	19.81%	27.61%	50.03%	18.58%	45.96%	32.07%
2015	15.13%	51.88%	28.13%	12.88%	64.18%	18.19%
2016	3.86%	79.31%	11.48%	2.71%	83.43%	9.36%

The estimated default probabilities, for the loans with grade D, are the following:

a) $\pi_{36\ Months}$ = 19.55%
b) $\pi_{60\ Months}$ = 26.24%

- Default Probability: Grade E

Table 22: Loans Status by Year and Term (Grade E).

Issue Date	Term: 36 Months			Term: 60 Months		
	Charged Off	**Current**	**Fully Paid**	**Charged Off**	**Current**	**Fully Paid**
2010	19.65%	0	80.35%	27.64%	0	72.36%
2011	20.59%	0	79.41%	28.29%	0	71.64%
2012	21.89%	0	78.11%	32.68%	14.64%	51.09%
2013	23.31%	0	76.69%	26.89%	27.32%	43.12%
2014	25.30%	34.50%	36.80%	25.64%	39.46%	31.08%
2015	18.18%	53.75%	22.36%	17.27%	55.96%	20.92%
2016	5.98%	74.70%	12.30%	5.12%	76.06%	12.25%

In relation to the loans with grade E, we estimate the following default probabilities:

a) $\pi_{36\ Months}$ = 21.36%
b) $\pi_{60\ Months}$ = 27.97%

- Default Probability: Grade F

Table 23: Loans Status by Year and Term (Grade F).

Issue Date	Term: 36 Months			Term: 60 Months		
	Charged Off	**Current**	**Fully Paid**	**Charged Off**	**Current**	**Fully Paid**
2010	29.67%	0	70.33%	31.82%	0	68.18%
2011	24.07%	0	75.93%	32.19%	0	67.81%
2012	18.45%	0	81.55%	34.90%	12.62%	49.50%
2013	26.81%	0	73.19%	31.81%	23.17%	42.19%
2014	27.27%	26.16%	43.94%	30.38%	32.31%	33.16%
2015	27.29%	41.31%	24.58%	25.17%	45.97%	22.36%
2016	10.91%	67.34%	12.56%	7.89%	70.26%	12.83%

For loans with grade F, we derive the following default probabilities:

a) $\pi_{36\ Months}$ = 24.75%
b) $\pi_{60\ Months}$ = 32.00%

- Default Probability: Grade G

Table 24: Loans Status by Year and Term (Grade G).

Issue Date	Term: 36 Months			Term: 60 Months		
	Charged Off	**Current**	**Fully Paid**	**Charged Off**	**Current**	**Fully Paid**
2010	35.3%	0	64.7%	32.32%	0	67.68%
2011	40.00%	0	60.00%	32.12%	0	67.88%
2012	16.67%	0	83.33%	43.04%	11.81%	44.30%
2013	26.67%	0	73.33%	32.74%	21.55%	42.52%
2014	32.40%	22.35%	41.34%	35.72%	27.69%	32.14%
2015	33.87%	37.50%	24.19%	30.69%	36.74%	25.85%
2016	17.17%	58.49%	13.77%	10.34%	66.55%	12.52%

The estimated default probabilities, related to loans with grade G, are the following:

a) $\pi_{36\ Months}$ = 29.66%
b) $\pi_{60\ Months}$ = 32.22%

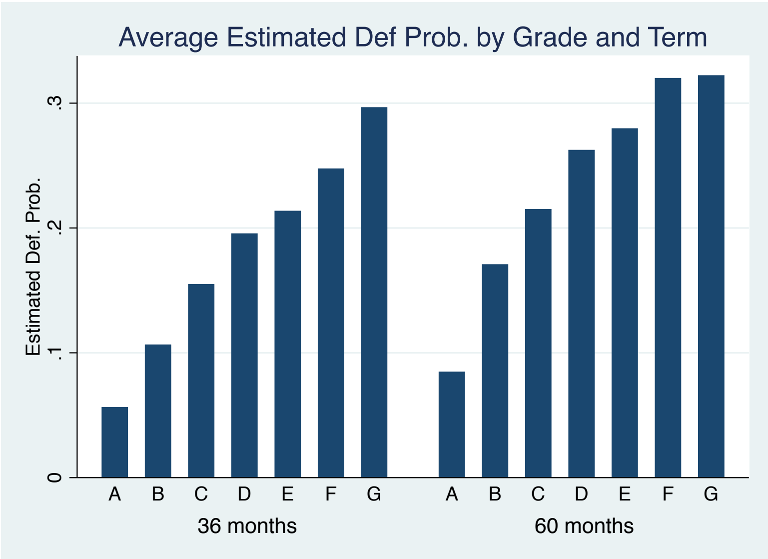
All the default probabilities we just estimated, in relation to the two available maturities and the seven different grades, are summarized in Table 25. As we expected, the estimated default probability increases with the grades, reflecting the higher riskiness of the borrower.

Table 25: Summarization of the Estimated Default Probability by Grade and term.

Estimated Default Probability		
Grade	**Term: 36 Months**	**Term: 60 Months**
A	5.64%	8.47%
B	10.64%	17.08%
C	15.48%	21.50%
D	19.55%	26.24%
E	21.36%	27.97%
F	24.75%	32.00%
G	29.66%	32.22%

To better compare the default probability associated to each loan, depending on grade and maturity, we plot a bar chart, reported in Figure 8. It is possible to observe that all grades point out a higher estimated default probability when maturity is 60 months, compared to the ones estimated with a 36 month maturity.

Figure 8: Average Default Probability, Divided by Maturity and Grade Category.



Finally, we summarize the information about the distribution of the average default probability we computed for the period of interest. For this sample, the mean of the default probability is 8.44%. The distribution of the estimated default probability is summarized in Table 26.

Table 26: Distribution of the Estimated Default Probability.

Estimated Default Probability Summarization			
	All Terms	**Term: 36 Months**	**Term: 60 Months**
Mean	15.58%	12.37%	23.54%
Std. Dev.	0.0705641	0.0489703	0.0500005
Min.	0.0564	5.64%	8.47%
25^{th} pcl.	10.64%	10.64%	8.47%
50^{th} pcl.	15.48%	10.64%	21.5%
75^{th} pcl	21.36%	15.48%	27.97%
Max.	32.22%	29.66%	32.22%
Number of Observations	1,313,570	936,387	377,183

3.1.5 Risk Adjusted Interest Rate

For each loan, given the corresponding interest rate and the estimated default probability, we compute the risk adjusted interest rate. This is an important measure of return which helped us define how much risk, in terms of default probability, is involved in producing that return, with reference to the risky rate. The formula we apply is the following:

$$1 + r = (1 - \pi) \times (1 + i) + \pi \times RR$$

where *r* is the risk-adjusted interest rate, *i* is the risky rate paid by the borrower and received by the lender, π is the probability of default we just estimated and RR is the recovery rate. To apply this formula, we estimate a value for the recovery rate (RR) that has to be associated to each loan, in relation to the corresponding grade. The recovery rate explains what is the percentage of the loan's face value, which is recovered in case of default. The variables from the pooled cross section dataset, that we employ for determining the RR, as scripted, are the following:

- *loan_amnt*: amount of issued loan
- *grade*: the grade assigned to the loan by Lending Club, according to the borrower's creditworthiness
- *recoveries*: the amount of gross recovery, concerning those loans that past in status *Charged Off* or *Does not meet credit policy: charge off*
- *tor_rec_prncp*: amount of principal collected, until Dec-16.

For each charged off loan, we determine the percentage of the recovery rate by applying the following formula:

$$RR_i = \frac{tot\_rec\_prncp_i + recoveries_i}{loan\_amnt_i}$$

Then, dividing by grade, we calculate the mean of the just estimated recovery rates, obtaining seven values of RR (from grade A to G) that we associate to each loan, in relation to the proper level of creditworthiness. The results of the recovery rate are summarized in Table 27.

Table 27: Estimated Recovery Rate.

Grade	Recovery Rate
A	42.34%
B	39.54%
C	33.82%
D	30.27%
E	25.27%
F	22.78%
G	20.22%

Therefore, once we got the RR, we acquired all the elements to apply the formula described above and we proceed estimating, for each issued loan, the corresponding risk adjusted interest rate. We summarize, in Table 28, some useful statistics about the estimated risk adjusted interest rate, including all the loans issued during the period of interest.

Table 28: Distribution of the Risk Adjusted Interest Rate.

Estimated Risk Adjusted Interest Rate	
Mean	0.42%
Std. Dev.	0.0348366
Min.	-21.64%
25th pcl.	-1.68%
50th pcl.	1.57%
75th pcl	3.17%
Max.	6.16%
Number of observations	1,313,570

The estimated risk adjusted interest rate ranges between 6.16% and -21.64%. The mean of the risk adjusted interest rate, computed considering all the loans displayed in the pooled cross section dataset, is 0.42%. This is very low, if compared to the mean of the risky interest rate paid by the borrowers, equal to 11.99%.

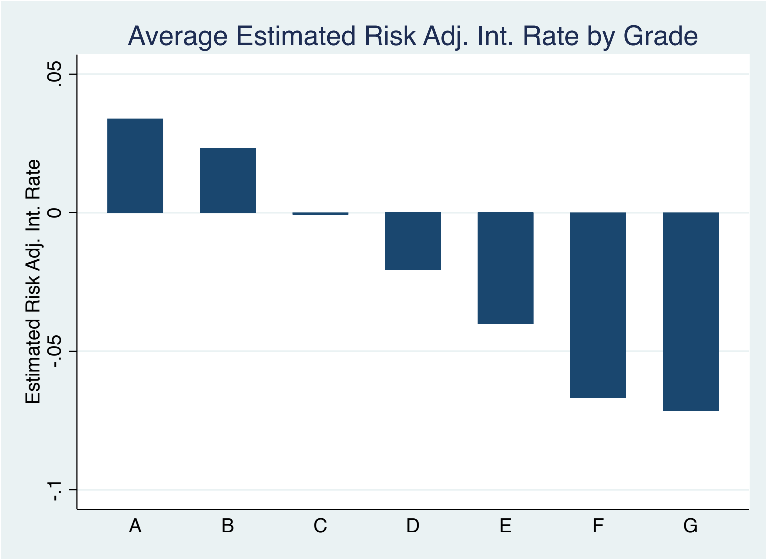
Then, we also summarize the results of the computations of the estimated risk adjusted interest rate, providing, for each grade and maturity, the corresponding mean. Table 29 reports the results of these calculations.

Table 29: Mean of the Estimated Risk Adjusted Interest Rate by Grade and Term.

Grade	Mean of the Estimated Risk Adjusted Interest Rate		
	All Terms	Term: 36 Months	Term: 60 Months
A	3.39%	3.43%	2.28%
B	2.32%	3.08%	-1.62%
C	-0.06%	1.47%	-3.19%
D	-2.06%	0.45%	-5.35%
E	-4.01%	0.30%	-6.08%
F	-6.69%	-0.74%	-8.21%
G	-7.16%	-4.49%	-7.56%

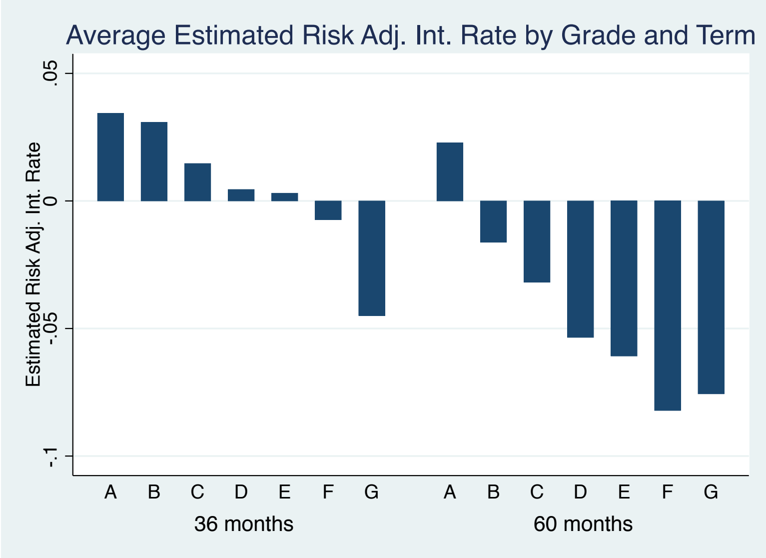
Looking at the means, divided by grade and calculated including loans of all maturities, the risk adjusted interest rate ranges from 3.39% (grade A), to -7.16% (grade G). Observing the bar charts reported in Figure 9, we clearly perceive the downward trend that characterizes the risk adjusted interest rate. Only loans having grade A and B have a positive mean of the risk adjusted interest rate. The negative sign accompanying the mean of the interest rate adjusted for risk, characterizing those loans with grade C, D, E, F and G, means that the borrowers' interest rate applied by Lending Club is not adequately high in relation to the portion of risk that is involved. Lenders investing in such loans, on average, will probably suffer losses.

Figure 9: Mean of the Estimated Risk Adjusted Interest Rate by Grade Category.



If, instead, we compute the means of the risk adjusted interest rate, not only dividing it by grade, but also by term, the results and the evidence that we obtain are slightly different. The bar chart in Figure 10 helps us understand and point out these differences. The first and immediate indication is that, regardless of the loans grade, the mean of the risk adjusted interest rate is always higher in relation to those credits having the shorter term, 36 months, compared to those with a 60 month maturity. This is strictly connected to the default probability that we found in Section 3.1.4: indeed, we observed that the probability of default we estimated is higher in loans with a 60 month maturity. In both cases, the mean of the risk adjusted interest rate follows a down trend, decreasing with the grades. Focussing on loans with a 36 month maturity, the mean of the risk adjusted interest rate scales from 3.43% (grade A) to -4.49% (grade G) and only those loans fitting with the category F and G have negative values. Differently, regarding only loans with a 60 month maturity, the mean of the risk adjusted interest rate is somewhat lower. First, the means of the interest rates adjusted for the implied risk range from 2.28% (grade A) to -8.21% (grade F). In addition, only credits identified with A reveal positive values of the mean of the risk adjusted interest rate.

Figure 10: Mean of the Estimated Risk Adjusted Return by Maturity and Grade Category.



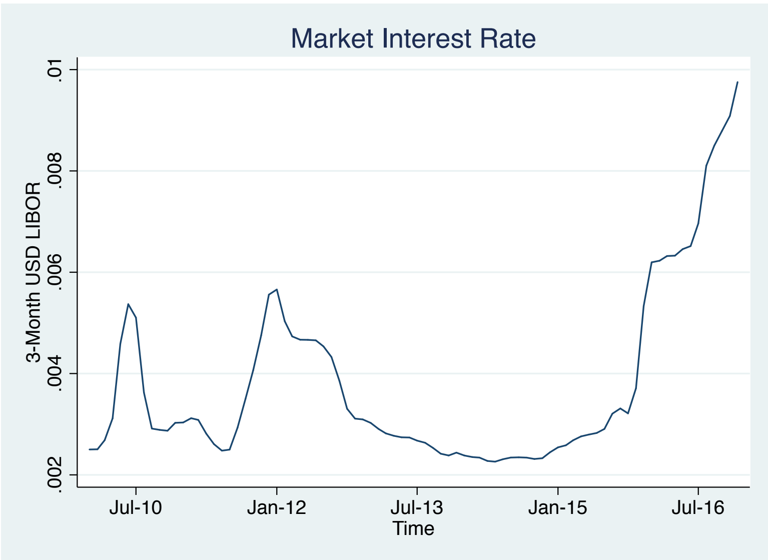
Therefore, from the lender's point of view, it is much less convenient not only to invest in loans with a 60 month maturity rather than a 36 month's, but also to provide their capital to borrowers having the highest grade and, as a consequence the highest risk profile. The indication deriving from the computation of the risk adjusted return is that the additional interest rate required to riskier borrowers is not adequate to compensate the additional riskiness of the agents reflecting the higher-grade category. This means that the interest rate Lending Club applies for most of the loans is too low, if compared to the corresponding risk, measured in terms of default probability. The algorithm the company uses to compute the borrowers' solvency rating would not possibly work so efficiently. Thus, the rating, and consequently the interest rates applied to borrowers, could not be appropriate in relation to riskiness and default probability.

3.2 3-Month USD LIBOR

Since we are interested in observing how Lending Club's credit provision reacts as marginal cost of funding changes, we collect historical data of 3-Month USD LIBOR, in relation to the period of interest, January 2010-December 2016. LIBOR, standing for London Interbank Offered Rate, is a benchmark rate that some of the world's leading banks charge one another for short-term loans. It serves as the first step to compute interest rates on various loans throughout the world. It is daily computed by the British Bankers' Association[16], based on five different currencies: U.S dollar (USD), Euro (EUR), pound sterling (GBP), Japanese yen (JPY) and Swiss franc (CHF). LIBOR can have seven different maturities: overnight, one week, and 1,2,3,6 and 12 months. In this study, we are interested in observing how it influences Lending Club's credit provision. Hence, we use 3-Mont USD LIBOR, which is also the most commonly quoted rate. It represents the marginal cost of funding in the U.S and, indeed, is the world's most widely-used benchmark for short-term interest rates. Its primary function is to serve as benchmark reference rate for debt instruments.

Using Federal Reserve Economic Data (FRED)[17], we download data of 3-Month USD LIBOR with monthly frequency. From the time series plot reported in Figure 11, it is possible to observe the 3-month USD LIBOR's trend: the most recent period clearly shows an up-trend; the highest values were reached at the end of 2016.

Figure 11: Trend of the 3-Month USD LIBOR, as Market Interest Rate.



[16] A trade association for the UK banking and financial sector, merged from 1st July 2017 into UK Finance.
[17] It is a database maintained by the Research division of the Federal Reserve Bank of St. Louis.

The distribution of 3-Month USD LIBOR is summarized in Table 30. The number of observations we collected is 84, one for each month from January 2010 to December 2016. The 3-Month USD LIBOR's mean is 0.3815461%.

Table 30: Distribution of the 3-Month USD LIBOR.

3-Month USD LIBOR	
Mean	0.3815461%
Std. Dev.	0.1789552
Min.	0.22609%
25th pcl.	0.23138%
50th pcl.	0.302665 %
75th pcl	0.46667 %
Max	0.97533%
Number of observations	84

Our goal is to estimate how variations in marginal cost of funding, represented by 3-month USD LIBOR, affect Lending Club's credit provision. Therefore, each loan has been associated with the corresponding value of 3-Month USD LIBOR interest rate. Hence, looking at the time variable *issue_*d, from the pooled cross section dataset, we relate each loan with the proper level of 3-Month USD LIBOR, matching month and year of issuance. In Appendix I, we report a table collecting all the values of the 3-Month USD LIBOR observed for each month, from January 2010 to December 2016.

3.3 Control Variables

To obtain better estimates of the Lending Club credit provision's reaction to changes of the marginal cost of funding, we introduce in the regressions three control variables: unemployment, Consumer Price Index (CPI) and Gross Domestic Product (GDP) growth. Indeed, as macroeconomic indicators, they could effectively influence P2P loans provision, even if they are not of prime interest in the analysis. Thus, although they enter the regression in the same way as the other independent variables, their interpretation is different. They are related to the dependent variable, credit provision, but we are not particularly interested in assessing how they affect Lending Club's loan volume. However, these control variables could effectively influence the results of the study and are therefore kept constant to test the relative relationship among the dependent and independent variables of interest.

3.3.1 Unemployment

Clearly, one of the factors that could influence P2P lending, but also the traditional channels of credit provision, is the rate of unemployment. Hence, by using Federal Reserve Economic Data (FRED) as data provider, we download the monthly series of unemployment rate registered in the Unites States during the period of interest. "Unemployment rate" is here defined as the number of unemployed as a percentage of the labor force. Then, each loan in the pooled cross section has been linked to the corresponding unemployment monthly rate, according to the variable *issue_d.*

3.3.2 Consumer Price Index

Another macroeconomic variable which could influence credit provision is the inflation rate which describes the trend of the general price level of goods and services. There are various indexes that can be used to measure inflation. We decide to measure the inflation rate with Consumer Price Index for All Urban Consumers (CPI), including all items. This is a measure of the average monthly change in the price for goods and services paid by urban consumers, including roughly 88% of the total population. This index is based on prices for food, clothing, shelter and fuels. Thus, by recurring to the Federal Reserve Economic Data, we download the corresponding series with monthly frequency. The data about Consumer Price Index, that we attach to the dataset about Lending Club loans, are transformed as log-difference. Even in this case, we use the variable *issue_d* from the pooled cross section to connect each loan to the corresponding value of inflation.

3.3.3 Gross Domestic Product Growth

Finally, we also include as control variable the growth of the Gross Domestic Product (GDP). As usual, this variable represents a monetary measure of the market value of all final goods and services produced in a certain period. Since GDP estimates are commonly used to determine the economic performance of a whole country or region, they could impact the channels of credit provision. So, we download from Bureau of Economic Analysis[18] the series of the Nominal GDP Growth, measured as percentage change from preceding period, considering the period of interest, from Jan-2010 to Dec-2016. However, the dynamics of this variable are not provided with frequencies less than quarterly[19]. Hence, to be consistent with the frequency of the loans we interpolate the GDP Growth for all intermediary months. We apply a cubic spline interpolation[20], thus obtaining monthly observations for GDP Growth too. Then, according to its *issue_d*, each loan has been associated with the corresponding monthly value of GDP Growth.

[18] It is part of the United States Department of Commerce and is a government agency that provides official macroeconomic and industry statistics.
[19] It is a common problem economists face with time series data. Most regression models require consistent time intervals and so it is necessary to get the data into the same frequency.
[20] It is a special case for spline interpolation that provides an interpolating polynomial that allows to split quarterly data into monthly.

Chapter 4

How Lending Club's Loan Volume Reacts to the Market Interest Rate

This chapter represents the central body of the analysis and contains the empirical evidence that we discover about the relationship between the market interest rate and Lending Club's loan volume. In the first section of this chapter, we summarize the objectives of the study, explaining the econometric techniques that we apply to the original dataset, the pooled cross section, and to its manipulations and aggregations, panels and time series. Then, we present the results, providing our interpretations. First, we focus on the market interest rates' effect on then individual loan size and on the loans provision clustered by address state and grade category. Then, we verify how the marginal cost of funding affects the total monthly amount of market-based lending provision.

4.1 Objectives

The scope of this analysis is to understand how Lending Club's loans provision is influenced by the market interest rate, that we associated with the 3-Month USD LIBOR. We investigate it by following two different approaches:

- We assess the impact of the interest rates on the individual loan size, implementing the regression estimates on the original pooled cross-section. We also verify the relationship with the market interest rate when loans are grouped together by address state or grade category, working separately on two different panels.
- We evaluate the influence of the marginal cost of funding on the total credit amount, at monthly level, applying a macro approach on data aggregated as a time series.

4.1.1 Datasets and Econometric Method

The econometric techniques we use to estimate the sensitivity of the credit provision from Lending Club are based on quantitative methods suitable for the datasets' characteristics on which we implement the analysis. The original dataset, downloaded from Lending Club's website and rearranged to include data on loans issued from January 2010 to December 2016, constitutes a pooled cross section. Furthermore, to analyse the market interest rate's impact on individual loan size, we also replicate the estimations, manipulating the original dataset to obtain two different panels, clustered by address state and grade. Differently, to verify the relation between interest rates and total loan amount, at monthly level, we develop this study aggregating the original pooled cross section dataset to obtain a time series. Before explaining the econometric techniques adopted, however, it can be useful to understand the characteristics and peculiarities of these three typologies of datasets:

- Pooled cross section: it is the dataset composed of the files available through the Lending Club's website. It has been obtained by simply aggregating all the available data to include the observations for the period of interest, ranging from January 2010 to December 2016. Since it has both cross-sectional and time series features, it is a pooled cross section. This is composed of observations about the loans amount, received by different borrowers, at different points in time. Each issued loan is described by several variables, which vary with time and in relation to the specific characteristics of the borrowers. So, we have independent cross sections reporting the loan amount (*loan_amnt*) and the time dimension (*issue_d*) describing the month in which each loan has been issued. The original dataset can be defined as a cross sectional dominant because the cross section units, *loan_amnt*, are more numerous than spatial units, *issue_d*.
- Panel: to improve the completeness of this study, we also perform the econometric analysis by transforming the original dataset, aggregating

the observations to obtain a panel. A panel data, or longitudinal data, consists of a time series for each cross-sectional member in the dataset. The key feature of a panel, which distinguishes it from a pooled cross section, is that the same cross-sectional units are followed over a given time period. We combine the observations of the original dataset and create two different panels: one having the address state (*addr_state*) of the loans as cross-sectional member, the other with the grade (*grade)* as entity unit. In both cases, the time variable involved is the variable *issue_d*, reporting the month of issuance. As pooled cross section, panels are used to test the loan's volume sensitivity, aggregated per address state or grade, to the market interest rate.

- Time series: a collection of observations of a variable, or several variables, over time. To transform the pooled cross section into a time series, we manipulate it, to obtain one observation for each time dimension (*issue_d*). The data frequency for the dataset, rearranged as a time series, is monthly: the variable *issue_d* registers the month in which each loan is issued. A key feature of time series data, which needs to be checked meticulously, is that this economic data rarely can be assumed to be independent across time. Most economic, but not only, time series are often related to their recent histories. Estimates with time series approach are performed to assess the total credit amount's sensitivity, aggregated with monthly frequency, to market interest rate.

Once understood the different structures of the datasets on which we work, we can provide some indications about the econometric method that we adopt. The estimation technique applied is the generic linear regression model, estimable by Ordinary Least Squares (OLS). Wherever possible, in order to provide better interpretations of the estimates, we also determine the values of the standardized coefficients. These allow us to better compare the weight and the impact of the included exogenous variables: the higher the absolute value of the standardized coefficient, the greater the effect of the independent variable on the dependent one.

Vice versa, the closer the coefficient to 0, the weaker the effect of such independent variable. All the estimates are performed with and without the previously identified control variables. In relation to the typologies of datasets on which we work, we verify the necessary assumptions and apply the required techniques in order to obtain unbiased, efficient and consistent estimators. First, to verify the absence of multicollinearity among the independent variables included in the estimates, we elaborate the correlation matrix. The values of this matrix allow us to understand the degree of linear relationship among the independent variables and can help us identify the potential presence of multicollinearity, which could erratically change the coefficient estimates. The indexes of the correlation matrix, reported in Table 31, highlight the absence of perfect linear dependence, and therefore reveal the non-existence of multicollinearity.

Table 31: Correlation Matrix Among the Independent Variables Involved in the Regressions.

	USD LIBOR	Interest Rate	Default Probability	GDP Growth	Unemployment	CPI
USD LIBOR	1					
Interest Rate	-0.019	1				
Default Probability	-0.044	0.887	1			
GDP Growth	-0.158	0.055	0.034	1		
Unemployment	-0.512	0.074	-0.006	0.146	1	
CPI	0.415	0.028	-0.014	-0.016	-0.042	1

Estimates on the pooled cross section dataset are performed adopting OLS regressions. The issued loans' amounts are independent of each other, which means that no correlation could bias the evaluations: indeed, each loan is observed only once in time and there is no way to identify those who apply. However, to avoid any possible heteroscedasticity, we add the specification of robust standard errors.

Performing the estimates on the panel datasets, we apply again the OLS regressions but, in addition, to obtain better and more precise estimates, we add Fixed Effect (FE) and Errors Clustering specifications. FE allows to explore the relationship between predictor and outcome variables within an entity[21] (country, person, company etc.). It assumes that something within the individual may impact or bias the predictor or outcome variables. Hence, FE removes the effect of those time-invariant characteristics, so we can assess the net effect of the predicators on the outcome variable. In this analysis with panel datasets, we apply FE to control for the address state's entities provided by the borrowers (*addr_state*) and of the grade category (*grade*). Furthermore, to improve the estimations' accuracy, all the estimated coefficients include the option of standard errors clustered by panel entity. Clustered standard errors are a way to obtain unbiased standard errors of OLS coefficients under a specific kind of heteroscedasticity. This technique is justified if there are several different covariance structures within the data, that vary in relation to a specific cluster, as with the panels which we elaborated.

Finally, in relation to the estimations performed on time series, we adopt OLS regression adding the specification of robust errors to heteroscedasticity. Moreover, to avoid possible autocorrelation problems, we also perform the regression estimates including an AR(1) process.

21 For example, the political system of a country or its barriers, could influence the dynamics of imports and exports or also the Gross Domestic Product.

4.1.2 Dependent and Independent Variables

To investigate how the loan provision, as individual loan size and as total credit amount, reacts to interest rates, we apply the theoretical backgrounds and illustrations proposed by Stiglitz and Weiss in *"Credit Rationing in Markets with Imperfect Information"*, whose conclusions and results are summarized in Chapter 2. Hence, the theoretical support for all the performed estimates is a reduced form model of consumer credit, where the credit provision is expressed by a linear function of interest rates and risk, having the following form:

$$K = f(i, \pi, e)$$

Looking at the model above, K is the dependent variable representing the credit provision's volume. The independent variables i, π and e are, respectively, the interest rate, risk profile of the borrower, in terms of default probability, and the market interest rate, as 3-Month USD LIBOR.

When we operate with the pooled cross section dataset we adopt, as dependent variable *K*, *log_loan_amnt*. This is the log-transformation of the variable *loan_amnt* described in Section 3.1.2, which defines the amount of Dollars of each individual loan issued through the Lending Club's platform during the period of interest. The independent variables we select from the pooled cross section are identified as: *int_rate, def_prob* and *libor_USD*, respectively standing for i, π and e. The first one, i, collects the interest rate that is applied to each loan. Statistics about the interest rates are described in Section 3.1.2. The second independent variable, π, is denoted in the pooled cross section dataset as *def_*prob. This is the variable we estimated in Section 3.1.5, which describes the likelihood of a default over the loan's period of length and is strictly connected to the borrower's characteristics. The last independent variable, e, described in Section 3.2, is *libor_USD*, representing the 3-Month USD LIBOR used to proxy the market interest.

Analogously, making the estimations on panels and time series, we adopt the same dependent and independent variables, but manipulated and rearranged according to the configuration of these datasets. Indeed, we set as panels' dependent variable the log-transformation of the total monthly amount of issued loans, divided by address state or grade. The independent variables, differently clustered by address state or grade, are the monthly mean of the interest rate and of the default probability, both weighted for the loan amount. In the time series, we establish as dependent variable the log-transformation of the total monthly amount of issued loans. Similarly, the independent variables adopted with the time series approach are determined as the monthly means of the interest rate and of the default probability, weighted for the loan amount, but without grouping them together by address state or grade. The market interest rate, 3-Month USD LIBOR, either with panels or with time series, is matched to the corresponding observation, according to the time variable *issue_d*.

Finally, to improve the precision of these estimates, we add the following control variables to all the datasets on which we operate: GDP Growth, inflation and unemployment, which are described in Section 3.3. These are treated as the other independent variables even if they are not of primary interest in this study. However, they are macroeconomic indicators that could effectively influence the Lending Club's loan provision. Again, once the control variables have been collected with monthly frequency, we attach them to the datasets, in relation to the time variable *issue_d*, matching year and month of issuance.

4.2 Impact of the Market Interest Rate on the Individual Loan Size

In this section, we investigate the relationship between loan provision and interest rates from an individual point of view. Indeed, here we perform the estimations on the pooled cross section dataset and on the panel datasets that we separately grouped by address state or by grade. Hence, operating on the pooled cross section, we verify in what way the size of each individual loan is influenced by the market interest rate, the 3-Month USD LIBOR. Analogously, we repeat the same procedure on the panel datasets that we derive from the original pooled cross section. Estimations on the panel datasets reveal the degree and strength of dependence between the loan provision, clustered in relation to the borrowers' characteristics, address state or grade, and market interest rate.

4.2.1 Pooled Cross Section Estimates

To investigate the relationship among loan volumes, interest rate, risk and marginal cost of funding, we start the analysis by simply implementing an OLS regression on the pooled cross section. Our objective is to identify the relationship between each single loan provision and the market interest rate, examining how this influence single loan sizes. We investigate how the amount of each individual loan is affected by changes in the market interest rate. Thus, we proceed estimating the coefficients of the following model:

$$\log(K_i) = \alpha_0 + \alpha_1 i_i + \alpha_2 \pi_i + \alpha_3 e_i + u_i$$

The dependent variable, $\log(K_i)$, is the log-transformation of the amount of each issued loan. The independent variables, i_i and π_i, are respectively the interest rate and the default probability associated to each individual loan, while e_i is the 3-Month USD LIBOR (*libor_USD*), exactly matching year and month of issuance of each loan. Finally, u_i is a random error term. The estimation outputs, including the specification of robust errors to heteroscedasticity, are reported in Table 32:

Table 32: Estimation Output of the Pooled Cross Section Estimate, without the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable	Standardized Coefficients
	log(loan)	
USD LIBOR	-5.578251^{***} (0.2562857)	-0.0187705
Interest Rate	-7.179943^{***} (0.0258411)	-0.4840774
Default Probability	6.437032^{***} (0.0152308)	0.6686923
Constant	9.371322^{***} (0.0020675)	
FE	No	
Errors Clustering	No	
R^2	0.1083	
Observations	1,313,570	

All estimated coefficients are significantly different from zero. Their p-values allow to reject the null hypothesis that these estimated coefficients may be zero, even at the 1% significance level. The standardized coefficient of USD LIBOR is equal to -0.0187705. This is characterized by a negative sign, which means that the market interest rate has a negative impact on the individual size of the loans issued through the Lending Club's platform. This empirical evidence allows us to state that the decrease of USD LIBOR induces investors to increment the amount of money they are willing to invest in Lending Club loans. Therefore, this could be interpreted in terms of better investment opportunities on offer: indeed, Lending Club, and P2P in general, offers the possibility to invest in assets generating higher returns compared to the other alternative and comparable financial instruments, for example bank deposits. Hence, when marginal cost of funding decreases, the attractiveness of P2P platforms, as alternative investment vehicles, becomes stronger. Consequently, investors, thanks to higher returns offered by P2P platforms, increment the amount of money they are willing to lend to P2P borrowers, causing the individual loans size to increase.

Then, in order to obtain better and more precise estimates of the individual loan volume's sensitivity to the market interest rate, we add the control variables to the previous estimated model: unemployment, inflation, in terms of the log-difference of the Consumer Price Index (CPI), and GDP Growth which we respectively indicated in the model as *un*, *inf* and *GDP*. So, the model we estimate has the following structure:

$$\log(K_i) = \alpha_0 + \alpha_1 i_i + \alpha_2 \pi_i + \alpha_3 e_i + \alpha_4 un_i + \alpha_5 inf_i + \alpha_6 GDP_i + u_i$$

The results of the estimations, including the standardized coefficients and the option of robust errors to heteroscedasticity, are summarised in Table 33:

Table 33: Estimation Output of the Pooled Cross Section Estimate, Including the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable log(loan)	Standardized Coefficients
USD LIBOR	-8.778233^{***} (0.3351779)	-0.0295383
Interest Rate	-7.067251^{***} (0.0270366)	-0.4764796
Default Probability	6.369372^{***} (0.0159834)	0.6616637
GDP Growth	-0.3862623^{***} (0.0435161)	-0.007317
Unemployment	-0.0103937^{***} (0.0006746)	-0.0166522
CPI	0.7967259^{**} (0.3313315)	0.0022266
Constant	9.447153^{***} (0.0048194)	
FE	No	
Errors Clustering	No	
R^2	0.1085	
Observations	1,313,570	

Even this estimated model is characterized by significantly different coefficients from zero: p-values of the t-statistics associated to each estimated coefficient are largely near to zero. They are all significant at the 1% level, except for the level of inflation, CPI, significant at the 5% level. Focussing on the independent variable's coefficient representing the 3-Month USD LIBOR, equal to −0.0295383, the negative sign persists. Therefore, the interpretation we provided with the model estimated above, excluding the control variables, can be confirmed. Market interest rates negatively influence the size of the individual loans issued through the Lending Club's platform. Broadly speaking, these results prove that if the market interest rates decrease, the size of the individual P2P loans increases. In addition, this latter model outlines that the absolute value of the standardized coefficient of the 3-Month USD LIBOR is higher than the one derived disregarding the control variables (from 0.0187705 to 0.0295383). Thus, in this case, the impact of the market interest is even stronger.

4.2.2 Panel Estimates

The amount of each single loan provided to borrowers is also influenced by other entities that are explained in the original pooled cross section dataset as the address state of the borrowers or their grade category. So, we also implement this econometric analysis by manipulating and collapsing the original dataset in order to obtain a panel, differently accounting for the entities of the address state and grade. A longitudinal, or panel, dataset is one that follows a given sample of individuals over time, and thus it provides multiple observations on each individual in the sample. A panel is characterized by two entities: the time dimension and individual or cross-section unit. We perform the estimations by working separately on two different panels, having as cross-section units the loans' address state or their grade. The time dimension, in both types of panels, is the variable *issue_d*, expressing year and month of issuance of the groups of loans. Performing the estimations on these two panels, we assess how the Lending Club's loan volume, is influenced by the market interest rates, within the entities of address state and grade category.

4.2.2.1 Panels Grouped by Address State

To obtain a panel, we manipulate the pooled cross section dataset to have one observation for each month and state in which the loans have been issued. Therefore, month by month and state by state, we compute the total amount of issued loans, getting the variable $monthly\_loan\_amnt_{it}$. Then, we calculate the mean of the applied interest rate and of the related default probability, weighted for loan amount, generating the variables $wtd\_int\_rate_{it}$ and $wtd\_def\_prob_{it}$. Variable $libor\_USD$, having monthly frequency, is included in the panel looking at the variable *issue_d*, exactly matching year and month of each group of loans. Given that the control variables also have monthly frequency, we apply the same procedure to add them to the panel dataset. Then, we set *addr_state* as the entities or panels *(i)* and *issue_d* as the time variable (t), obtaining an unbalanced panel, because not all states have data (loans) for all months. This means that during some months, there are states which did not require any loan. However, this does not pose a problem for correctly implementing the estimations. Hence, since we are interested in exploring the relationship between predictors and outcome variable, within the entity of the address state, we apply the FE model. Initially, we investigate the effects of the variables of interests omitting the control variables. Therefore, the equation for the FE model that we estimate is the following one:

$$\log(k_{it}) = \alpha_0 + \alpha_1 e_{it} + \alpha_2 i_{it} + \alpha_3 \pi_{it} + u_{it}$$

The dependent variable $\log(k_{it})$ is the log-transformation of the variable $monthly\_loan\_amnt_{it}$, expressing the amounts of issued loans, grouped by address state. The independent variables i_{it}, π_{it} and e_{it} are, respectively, $wtd\_int\_rate_{it}$, $wtd\_def\_prob_{it}$ and 3-Month USD LIBOR, with α_1, α_2 and α_3 as relative coefficients, and u_{it} as error term. Notice that i equals entity (*addr_state*) and t equals time (*issue_d*). The results of the estimation, that we perform including the option of errors clustered by state (*addr_state*) are the following, represented in Table 34:

Table 34: Estimation Output of the Panel Estimate, Grouped by Address State, without the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable
	log(loan)
USD LIBOR	1.781547^{***} (0.0427964)
Interest Rate	23.5877^{***} (2.988649)
Default Probability	5.349314^{**} (2.012343)
Constant	9.360299^{***} (0.3941319)
FE (State)	Yes
Errors Clustering (State)	Yes
R^2	0.0843
Observations	3,776
Clusters	51

The estimated coefficients, except for the default probability, are all significantly different from zero at the 1% significance level. The default probability, given the value of its t-statistic, is significantly different from zero at the 5%. Differently from the models we estimated above with the pooled cross section, the coefficient associated to the independent variable expressing the 3-Month USD LIBOR, has a positive sign. This model suggests that, within the entity of the address state, market interest rates positively influence Lending Club loans: an increase in the marginal cost of funding determines an increase in the amount of loans issued, clustered by state. However, estimating the same FE model, but including the control variables, the results we achieve are different and confirm the evidence found with the pooled cross section analysis. Indeed, the model we estimate, adding the control variables, has the following structure:

$$\log(k_{it}) = \alpha_0 + \alpha_1 e_{it} + \alpha_2 i_{it} + \alpha_3 \pi_{it} + \alpha_4 un_{it} + \alpha_5 inf_{it} + \alpha_6 GDP_{it} + u_{it}$$

The results of the FE model's estimation, reported again with the option of standard errors clustered by address state, are represented in Table 35:

Table 35: Estimation Output of the Panel Estimate, Grouped by Address State, Including the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable
	log(loan)
USD LIBOR	-1.241001^{***} (0.0575323)
Interest Rate	20.28131^{***} (1.352995)
Default Probability	-5.908115^{***} (0.9904605)
GDP Growth	-0.1210645 (0.5266493)
Unemployment	-0.8839518^{***} (0.0090288)
CPI	31.21323^{***} (2.764712)
Constant	19.04877^{***} (0.2086139)
FE (State)	Yes
Errors Clustering (State)	Yes
R^2	0.5791
Observations	3,776
Clusters	51

All the estimated coefficients, except for the one related to the control variable GDP Growth, are meaningful even at the 1% significant level. The independent variable denoting the GDP Growth is without significance at all levels, even 10%. If compared to the model without the control variables, the sign of the estimated coefficient associated to the market interest rate, USD LIBOR, inverted the relationship with the dependent variable. Passing from the model excluding the control variables to the one including them, the R^2 coefficient of determination significantly augmented (from 0.0843 to 0.5791). Thus, the model estimated regarding the control variables is much more complete than the one excluding GDP Growth, Unemployment and Consumer Price Index. Therefore, considering this latter model more explicative, we conclude that, even when loans amount is clustered state by state, the market interest rate has a negative relationship with the aggregated amount of loans issuance.

4.2.2.2 Panels Grouped by Grade

Furthermore, we repeat the estimates performed in the section above, but now working on a panel in which data is not aggregated by address state but by grade. So, we manipulate the original pooled cross section to get a panel in which loans are grouped together by grade category. We start determining the monthly amount of issued loans, for the different grades, from A to G, getting the variable $monthly\_loan\_amnt_{it}$. Then, in relation to the different grades, we calculate the monthly mean of the interest rate and default probability, both weighted for the loan amount, generating the variables $wtd\_int\_rate_{it}$ and $wtd\_def\_prob_{it}$. We add the variable $libor\_USD$, matching year and month of issuance, explained in the variable *issue_d*. In this way, we have a longitudinal dataset, characterized by the variable *grade*, as panel entity, and *issue_d*, as time dimension. Even in this case, the panel is unbalanced, because there are no identical time periods for all cross-section observations: in detail, the only missing entity is represented by loans of grade G issued in May 2010. We attach the control variables to the dataset, in relation the variable *issue_d*. Therefore, initially ignoring the control variables, we estimate the following FE Model, to investigate the relationship between predictors and the outcome variable, within the entity of the grade associated to each loan:

$$\log(k_{it}) = \alpha_0 + \alpha_1 e_{it} + \alpha_2 i_{it} + \alpha_3 \pi_{it} + u_{it}$$

The dependent variable $\log(k_{it})$ is the log-transformation of the variable $monthly\_loan\_amnt_{it}$, expressing the amounts of issued loans, grouped by grade category. The independent variables i_{it}, π_{it} and e_{it} are respectively, $wtd\_int\_rate_{it}$, $wtd\_def\_prob_{it}$ and 3-Month USD LIBOR, with α_1, α_2 and α_3 as relative coefficients, and u_{it} as the error term. Notice that i equals entity (*grade*) and t equals time (*issue_d*). The results, estimated with standard errors clustered by grade category, are summarized in Table 36:

Table 36: Estimation Output of the Panel Estimate, Grouped by Grade Category, without the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable
	log(loan)
USD LIBOR	71.03195 (69.57404)
Interest Rate	34.33993*** (4.779431)
Default Probability	29.99543*** (6.605249)
Constant	3.723751* (1.727301)
FE (Grade)	Yes
Errors Clustering (Grade)	Yes
R^2	0.1744
Observations	587
Clusters	7

In this case, the evidence provided by the estimation outputs is meaningful. Indeed, the independent variable representing the market interest rate, USD LIBOR, given the value of its t-statistic, is not significant. Thus, we repeat the estimation of the FE model including the control variables, adding to the previous model the independent variables expressing unemployment (*un*), GDP Growth (*GDP*) and inflation (*inf*). We estimate the coefficients of the following model:

$$\log(k_{it}) = \alpha_0 + \alpha_1 e_{it} + \alpha_2 i_{it} + \alpha_3 \pi_{it} + \alpha_4 GDP_{it} + \alpha_5 un_{it} + \alpha_6 inf_{it} + u_{it}$$

The results, including the specification of standard errors clustered by grade, are represented in Table 37:

Table 37: Estimation Output of the Panel Estimate, Grouped by Grade Category, Including the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable
	log(loan)
USD LIBOR	-131.5349^{***}
	(6.910312)
Interest Rate	2.36304
	(3.362767)
Default Probability	8.603318
	(6.173837)
GDP Growth	0.8861873
	(1.13735)
Unemployment	-0.8280227^{***}
	(0.287867)
CPI	43.46598^{***}
	(11.1306)
Constant	20.25213^{***}
	(1.298893)
FE (Grade)	Yes
Errors Clustering (Grade)	Yes
R^2	0.1341
Observations	587
Clusters	7

The estimated coefficient associated to the variable USD LIBOR is significant even at the 1% level. The same goes for the constant and for the control variables expressing the inflation in terms of Consumer Price Index, and unemployment. However, the explanatory variables expressing the interest rate, default probability and GDP Growth, are not significant at all levels. Although the model is characterized by some relevant variables statistically not significant, USD LIBOR, the variable of primary interest in this analysis, is meaningful. Its coefficient has a negative sign, supporting the evidence we found in the estimations performed with the previous models: the market interest rate has a negative relationship with the loans amount, even when it is clustered and grouped together by grade category.

4.3. Impact of the Interest Rates on the Total Credit Amount

So far, we focussed on evaluating how the market interest rate influences the single loan provision and the amount of issued loans grouped together by address state and grade category. However, the present study also has the objective of verifying how the market interest rate affects the overall level of loan provision, as total credit amount at monthly level.

Therefore, to obtain these figures, we implement the regression estimates aggregating the pooled cross section, to have one observation for each *issue_d*. We then manipulate the data, transforming the pooled cross section into a time series. We fix, as dependent variable, the log-transformation of the total monthly amount of issued loans, $monthly\_loan\_amnt_t$. As independent variables of the regression, we use the monthly mean of the default probability, $wtd\_def\_prob_t$, and of the interest rate applied to borrowers, $wtd\_int\_rate_t$, both weighted for the loans amount. The other independent variable, representing the marginal cost of funding, is 3-Month USD LIBOR, included in the dataset at monthly level. The control variables are attached to the dataset in relation to each year and month of issuance. In this way, we obtain a time series and we fix *issue_d* as time variable. The estimation technique we use is the OLS, applied to time series data. In the models' estimation, we add the specification of robust standard errors. This procedure assumes the error structure to be heteroscedastic and auto-correlated up to some lag. First, we estimate the model, including only the independent variables of interest, without considering the control variables. So, the model we estimate has the following structure:

$$\log(k_t) = \alpha_0 + \alpha_1 i_t + \alpha_2 \pi_t + \alpha_3 e_t + u_t$$

The dependent variable, $\log(k_t)$, is the log-transformation of the variable $monthly\_loan\_amnt_t$. The independent variables, i_t, π_t and e_t, are, respectively, $wtd\_int\_rate_t$, $wtd\_def\_prob_t$ and *libor_USD*. Notice that all the variables involved are indexed with *t*, because we are now dealing with a time series. The results of the regression are reported in Table 38:

Table 38: Estimation Output of the Time Series Estimate, without the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable
	log(loan)
USD LIBOR	209.0539***
	(63.03787)
Interest Rate	38.04551***
	(14.05987)
Default Probability	25.63744
	(16.131)
Constant	8.2698984***
	(2.45749)
FE	No
Errors Clustering	No
R^2	0.1746
Observations	84

The estimation outputs highlight statistically significant coefficients at the 1% level, except for the explanatory variable of the default probability. The estimated coefficient associated to USD LIBOR has a positive sign, pointing out a positive relationship with the total amount of loans issued monthly. Nevertheless, to improve the precision of the estimates, we add the control variables, unemployment, GDP Growth and Consumer Price Index, estimating a model having the following structure:

$$\log(K_t) = \alpha_0 + \alpha_1 e_t + \alpha_2 i_t + \alpha_3 \pi_t + \alpha_4 un_t + \alpha_5 inf_t + \alpha_6 GDP_t + u_t$$

The results, performed with the option of robust errors to heteroscedasticity, are presented in Table 39:

Table 39: Estimation Output of the Time Series Estimate, Including the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable
	log(loan)
USD LIBOR	-125.0162^{***} (14.72203)
Interest Rate	22.25523^{***} (2.69905)
Default Probability	-8.364728^{***} (3.097803)
GDP Growth	0.1065126 (1.636841)
Unemployment	-0.8655932^{***} (0.0177357)
CPI	35.89532^{*} (21.28387)
Constant	23.47535^{***} (0.6541936)
FE	No
Errors Clustering	No
R^2	0.9723
Observations	84

The estimated coefficients, are all largely significant at all levels, except for the independent variable representing the Consumer Price Index, which is significant only at the 10%. Differently, the control variable expressing the GDP Growth is not relevant. First, we observe that the R^2 coefficient considerably augmented, from 0.1746 to 0.9723, suggesting that the addition of the control variables provide a more complete and exhaustive model. The sign of the market interest rate's coefficient, USD LIBOR, changed, becoming negative. So, since the model estimated with the inclusion of the control variables is more thorough, we can assert that, even when considering the amount of loans monthly aggregated, USD LIBOR negatively influences the overall credit issued through the Lending Club's platform.

Furthermore, to avoid possible autocorrelation problems, we perform the estimation adding an AR(1) process. Hence, initially excluding the control variables, we estimate the following model, where all the explanatory variables are lagged by one:

$$\log(K_t) = \alpha_0 + \alpha_1 \mathrm{e}_{t-1} + \alpha_2 i_{t-1} + \alpha_3 \pi_{t-1} + \alpha_4 \, log(K)_{t-1} + u_t$$

The results we obtained, including the option of robust standard errors to heteroscedasticity, are summarized in Table 40:

Table 40: Estimation Output of the Time Series Estimate, with all Explanatory Variables Lagged, but without the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable
	$\log(loan_t)$
USD LIBOR$_{t-1}$	-3.113707 (18.47939)
Interest Rate$_{t-1}$	2.163152 (2.530779)
Default Probability$_{t-1}$	-0.393349 (1.419178)
$\log(loan)_{t-1}$	0.9646181^{***} (0.0219194)
Constant	0.4876011 (0.3137509)
FE	No
Errors Clustering	No
R^2	0.9623
Observations	83

The estimation outputs we acquire are not good. Indeed, all the coefficients of the explanatory variables, except for $\log(loan)_{t-1}$, are not significant, not even at the 10% level. Thus, to improve the quality of these estimates, we try to improve the results of the estimations, including the control variables. The model we estimate has the following structure:

$$\log(K_t) = \alpha_0 + \alpha_1 e_{t-1} + \alpha_2 i_{t-1} + \alpha_3 \pi_{t-1} + +\alpha_4 un_{t-1} + \alpha_5 inf_{t-1} + \alpha_6 GDP_{t-1} + \alpha_7\, log(K)_{t-1} + u_t$$

The results of the estimations, again with the option of robust standard errors to heteroscedasticity, are exposed in Table 41:

Table 41: Estimation Output of the Time Series Estimate, with all Explanatory Variables Lagged and Including the Control Variables. (***) Represents Significance at the 1% Level, (**) at the 5% Level and (*) at the 10% Level. Standard Errors in ().

Independent Variables	Dependent Variable
	$\log(loan_t)$
USD LIBOR$_{t-1}$	-87.88641^{***}
	(29.90763)
Interest Rate$_{t-1}$	16.93674^{***}
	(4.316661)
Default Probability$_{t-1}$	-6.023614^{**}
	(3.067822)
$GDP\ Growth_{t-1}$	-0.278883
	(1.532631)
$Unemployment_{t-1}$	-0.6001423^{***}
	0.1549617
CPI$_{t-1}$	12.54318
	21.68007
$\log\,(loan)_{t-1}$	0.2898355^{*}
	(0.174614)
Constant	16.49986^{***}
	(4.217412)
FE	No
Errors Clustering	No
R^2	0.9761
Observations	83

The variable of primary interest, representing the marginal cost of funding, USD LIBOR, is now significant, even at the 1% level, as interest rate and unemployment. The default probability is statistically significant at the 5% level, while the remaining control variables, GDP Growth and Consumer Price Index, are still irrelevant at the 10% level. Focussing on the sign of USD LIBOR, the empirical evidence we find confirms what we stated above: a negative dependence between the market interest rate and the total amount of credit issued at monthly level. Hence, a decrease of the market interest rate also determines an increase, at monthly level, of the total amount of loans issued through the Lending Club's platform.

Conclusions

The objective of this thesis is to find the relationship between the market interest rate and P2P lending. We worked on Lending Club's loans data, as representative of P2P lending, and we adopted the 3-Month USD LIBOR, as the market interest rate.

We started describing the world of P2P lending to understand peculiarities and characteristics of this emerging branch of the FinTech revolution. Then, we define the conceptual framework on which this study is built: "*Credit Rationing in Markets with Imperfect Information*", a model developed by Stiglitz-Weiss, in 1981, which individuated the determinants of credit rationing. So, through this model, we derived a reduced form model of consumer credit, where loans provision depends on interest rate, default probability, and market interest rate, as 3-Month USD LIBOR. We describe some useful and meaningful characteristics of the datasets adopted for this study, and we explained the related manipulations and calculations that we made.

First, we estimated the default probability that, depending on maturity and grade category, can be associated to each loan. The results of these calculations reveal that Lending Club loans have high default probabilities, corresponding to an elevated likelihood of default over the period of length of the loan. Then, we computed the interest rate adjusted for the estimated future losses on loans. To perform these calculations, we first derived the recovery rate (RR), finding out that the percentage of the loan's face value that investors can recover in case of default is very low. The subsequent computations of the risk adjusted interest rate disclose very low values, and in some cases also negative ones, if compared to the risky interest rates paid by the borrowers. This means that the interest rate Lending Club applies for most of the loans is not appropriate in relation to the riskiness of the borrowers.

Then, we presented the empirical analysis and the econometric estimates that we performed on Lending Club loans to identify a relationship between the market interest rate and Lending Club loans provision. The results that we acquired suggest that the marginal cost of funding has a negative impact on the market-based lending. Therefore, if the 3-Month USD LIBOR decreases, credit provision through the Lending Club's platform increases. This evidence is confirmed in all the estimations we perform. Indeed, regressions on pooled cross section dataset reveal that 3-Month USD LIBOR causes an increment of the individual loans size. Analogously, this theory is confirmed by clustering separately the pooled cross section by address state and by grade category, obtaining two different panels. Moreover, the regression estimates derived by aggregating the original pooled cross section to have a time series also show that the total credit amount, at monthly level, has negative relationship with the market interest rate.

Finally, due to the magnitude of Lending Club, the world's largest P2P lending company, these results can be extended to the whole market-based lending in the U.S. Furthermore, given the growing impact and development of P2P lending in the recent years, mostly for new loans provision, the relationship between market interest rate, as a concern of monetary economics, and the P2P credit provision is destined to have a not-so-negligible impact on the monetary policy decisions. As we already described, the market share of P2P lending is still relatively low if compared to the incumbents, traditional financial institutions. However, the advantages and characteristics of the P2P lending business model, together with the development of new and even more efficient technologies, suggest that the growth of P2P lending is destined to continue in cooperation with the services provided by traditional banks. Therefore, the impact of P2P lending will be considerable not only in the credit market, but also in the monetary policy decisions. Policy makers, in their decision-making process, will also have to consider the effects of the market interest rate on P2P lending.

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Appendix

Appendix A – List of the Variables in the Datasets Downloaded from Lending Club

Variable name	Description
acc_now_delinq	The number of accounts on which the borrower is now delinquent.
acc_open_past_24mths	Number of trades opened in past 24 months.
addr_state	The state provided by the borrower in the loan application
all_util	Balance to credit limit on all trades
annual_inc	The self-reported annual income provided by the borrower during registration.
annual_inc_joint	The combined self-reported annual income provided by the co-borrowers during registration
application_type	Indicates whether the loan is an individual application or a joint application with two co-borrowers
avg_cur_bal	Average current balance of all accounts
bc_open_to_buy	Total open to buy on revolving bankcards.
bc_util	Ratio of total current balance to high credit/credit limit for all bankcard accounts.
chargeoff_within_12_mths	Number of charge-offs within 12 months
collection_recovery_fee	post charge off collection fee
collections_12_mths_ex_med	Number of collections in 12 months excluding medical collections
delinq_2yrs	The number of 30+ days past-due incidences of delinquency in the borrower's credit file for the past 2 years
delinq_amnt	The past-due amount owed for the accounts on which the borrower is now delinquent.
desc	Loan description provided by the borrower
dti	A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower's self-reported monthly income.

dti_joint	A ratio calculated using the co-borrowers' total monthly payments on the total debt obligations, excluding mortgages and the requested LC loan, divided by the co-borrowers' combined self-reported monthly income
earliest_cr_line	The month the borrower's earliest reported credit line was opened
emp_length	Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
emp_title	The job title supplied by the Borrower when applying for the loan.*
funded_amnt	The total amount committed to that loan at that point in time.
funded_amnt_inv	The total amount committed by investors for that loan at that point in time.
grade	LC assigned loan grade
home_ownership	The home ownership status provided by the borrower during registration or obtained from the credit report. Our values are: RENT, OWN, MORTGAGE, OTHER
id	A unique LC assigned ID for the loan listing.
il_util	Ratio of total current balance to high credit/credit limit on all install acct
initial_list_status	The initial listing status of the loan. Possible values are – W, F
inq_fi	Number of personal finance inquiries
inq_last_12m	Number of credit inquiries in past 12 months
inq_last_6mths	The number of inquiries in past 6 months (excluding auto and mortgage inquiries)
installment	The monthly payment owed by the borrower if the loan originates.
int_rate	Interest Rate on the loan
issue_d	The month which the loan was funded
last_credit_pull_d	The most recent month LC pulled credit for this loan
last_pymnt_amnt	Last total payment amount received
last_pymnt_d	Last month payment was received
loan_amnt	The listed amount of the loan applied for by the borrower. If at some point in time, the credit

	department reduces the loan amount, then it will be reflected in this value.
loan_status	Current status of the loan
max_bal_bc	Maximum current balance owed on all revolving accounts
member_id	A unique LC assigned Id for the borrower member.
mo_sin_old_il_acct	Months since oldest bank installment account opened
mo_sin_old_rev_tl_op	Months since oldest revolving account opened
mo_sin_rcnt_rev_tl_op	Months since most recent revolving account opened
mo_sin_rcnt_tl	Months since most recent account opened
mort_acc	Number of mortgage accounts.
mths_since_last_delinq	The number of months since the borrower's last delinquency.
mths_since_last_major_derog	Months since most recent 90-day or worse rating
mths_since_last_record	The number of months since the last public record.
mths_since_rcnt_il	Months since most recent installment accounts opened
mths_since_recent_bc	Months since most recent bankcard account opened.
mths_since_recent_bc_dlq	Months since most recent bankcard delinquency
mths_since_recent_inq	Months since most recent inquiry.
mths_since_recent_revol_delinq	Months since most recent revolving delinquency.
next_pymnt_d	Next scheduled payment date
num_accts_ever_120_pd	Number of accounts ever 120 or more days past due
num_actv_bc_tl	Number of currently active bankcard accounts
num_actv_rev_tl	Number of currently active revolving trades
num_bc_sats	Number of satisfactory bankcard accounts
num_bc_tl	Number of bankcard accounts
num_il_tl	Number of installment accounts
num_op_rev_tl	Number of open revolving accounts
num_rev_accts	Number of revolving accounts
num_rev_tl_bal_gt_0	Number of revolving trades with balance >0
num_sats	Number of satisfactory accounts
num_tl_120dpd_2m	Number of accounts currently 120 days past due (updated in past 2 months)

num_tl_30dpd	Number of accounts currently 30 days past due (updated in past 2 months)
num_tl_90g_dpd_24m	Number of accounts 90 or more days past due in last 24 months
num_tl_op_past_12m	Number of accounts opened in past 12 months
open_acc	The number of open credit lines in the borrower's credit file.
open_acc_6m	Number of open trades in last 6 months
open_il_12m	Number of installment accounts opened in past 12 months
open_il_24m	Number of installment accounts opened in past 24 months
open_il_6m	Number of currently active installment trades
open_rv_12m	Number of revolving trades opened in past 12 months
open_rv_24m	Number of revolving trades opened in past 24 months
out_prncp	Remaining outstanding principal for total amount funded
out_prncp_inv	Remaining outstanding principal for portion of total amount funded by investors
pct_tl_nvr_dlq	Percent of trades never delinquent
percent_bc_gt_75	Percentage of all bankcard accounts > 75% of limit.
policy_code	publicly available policy_code=1 new products not publicly available policy_code=2
pub_rec	Number of derogatory public records
pub_rec_bankruptcies	Number of public record bankruptcies
purpose	A category provided by the borrower for the loan request.
pymnt_plan	Indicates if a payment plan has been put in place for the loan
recoveries	post charge off gross recovery
revol_bal	Total credit revolving balance
revol_util	Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
sub_grade	LC assigned loan subgrade
tax_liens	Number of tax liens
term	The number of payments on the loan. Values are in months and can be either 36 or 60.

title	The loan title provided by the borrower
tot_coll_amt	Total collection amounts ever owed
tot_cur_bal	Total current balance of all accounts
tot_hi_cred_lim	Total high credit/credit limit
total_acc	The total number of credit lines currently in the borrower's credit file
total_bal_ex_mort	Total credit balance excluding mortgage
total_bal_il	Total current balance of all installment accounts
total_bc_limit	Total bankcard high credit/credit limit
total_cu_tl	Number of finance trades
total_il_high_credit_limit	Total installment high credit/credit limit
total_pymnt	Payments received to date for total amount funded
total_pymnt_inv	Payments received to date for portion of total amount funded by investors
total_rec_int	Interest received to date
total_rec_late_fee	Late fees received to date
total_rec_prncp	Principal received to date
url	URL for the LC page with listing data.
verification_status	Indicates if income was verified by LC, not verified, or if the income source was verified
zip_code	The first 3 numbers of the zip code provided by the borrower in the loan application.

Appendix B – Statistics about Loans Status for Grade A

Grade A				
	Term: 36 Months		Term: 60 Months	
Loan Status	**Frequency**	**Percent**	**Frequency**	**Percent**
Charged Off	5,503	2.64%	186	2.03%
Current	120,578	57.89%	6,981	76.11%
No Credit Policy: Charged Off	1	0	0	0
No Credit Policy: Fully Paid	25	0.01%	3	0.03%
Fully Paid	80,472	38.64%	1,910	20.82%
In Grace Period	581	0.28%	32	0.35%
Late (16-30 Days)	246	0.12%	15	0.16%
Late (31-120 Days)	877	0.42%	45	0.49%
Total	208,283	100%	9,172	100%

Appendix C – Statistics about Loans Status for Grade B

Grade B				
	Term: 36 Months		Term: 60 Months	
Loan Status	Frequency	Percent	Frequency	Percent
Charged Off	17,608	5.42%	2,958	4.75%
Current	176,338	54.31%	44,530	71.53%
Default	5	0	0	0
No Credit Policy: Charged Off	22	0.01%	6	0.01%
No Credit Policy: Fully Paid	107	0.03%	15	0.02%
Fully Paid	125,035	38.51%	13,744	22.08%
In Grace Period	1,852	0.57%	308	0.49%
Late (16-30 Days)	758	0.23%	117	0.19%
Late (31-120 Days)	2,946	0.91%	579	0.93%
Total	324,671	100%	62,257	100%

Appendix D – Statistics about Loans Status for Grade C

Grade C				
	Term: 36 Months		Term: 60 Months	
Loan Status	**Frequency**	**Percent**	**Frequency**	**Percent**
Charged Off	22,390	8.86%	9,971	8.09%
Current	135,123	53.48%	82,481	66.89%
Default	10	0	1	0
No Credit Policy: Charged Off	46	0.02%	8	0.01%
No Credit Policy: Fully Paid	184	0.07%	28	0.02%
Fully Paid	87,709	34.71%	27,479	22.29%
In Grace Period	2,278	0.90%	1,007	0.82%
Late (16-30 Days)	874	0.35%	432	0.35%
Late (31-120 Days)	4,070	1.61%	1,899	1.54%
Total	252,684	100%	123,306	100%

Appendix E – Statistics about Loans Status for Grade D

Grade D				
	Term: 36 Months		**Term: 60 Months**	
Loan Status	**Frequency**	**Percent**	**Frequency**	**Percent**
Charged Off	14,866	13.27%	11,161	13.08%
Current	51,759	46.19%	50,536	59.22%
Default	2	0	2	0.00%
No Credit Policy: Charged Off	63	0.06%	27	0.03%
No Credit Policy: Fully Paid	136	0.12%	46	0.05%
Fully Paid	41,159	36.73%	20,195	23.67%
In Grace Period	1,205	1.08%	1,008	1.18%
Late (16-30 Days)	530	0.47%	401	0.47%
Late (31-120 Days)	2,344	2.09%	1,957	2.29%
Total	112,064	100%	85,333	100%

Appendix F – Statistics about Loans Status for Grade E

Grade E				
	Term: 36 Months		Term: 60 Months	
Loan Status	**Frequency**	**Percent**	**Frequency**	**Percent**
Charged Off	5,457	17.56%	11,460	17.70%
Current	13,509	43.46%	33,437	51.65%
Default	1	0	3	0
No Credit Policy: Charged Off	14	0.05%	39	0.06%
No Credit Policy: Fully Paid	51	0.16%	64	0.10%
Fully Paid	10,589	34.07%	16,510	25.50%
In Grace Period	404	1.30%	958	1.48%
Late (16-30 Days)	186	0.60%	407	0.63%
Late (31-120 Days)	871	2.80%	1,861	2.87%
Total	31,082	100%	64,739	100%

Appendix G – Statistics about Loans Status for Grade F

Grade F				
	Term: 36 Months		Term: 60 Months	
Loan Status	**Frequency**	**Percent**	**Frequency**	**Percent**
Charged Off	1,385	21.10%	5,861	22.94%
Current	2,673	40.73%	11,184	43.77%
Default	2	0.03%	0	0
No Credit Policy: Charged Off	7	0.11%	18	0.07%
No Credit Policy: Fully Paid	19	0.29%	27	0.11%
Fully Paid	2,117	32.26%	6,964	27.25%
In Grace Period	104	1.58%	416	1.63%
Late (16-30 Days)	48	0.73%	200	0.78%
Late (31-120 Days)	208	3.17%	882	3.45%
Total	6,563	100%	25,552	100%

Appendix H – Statistics about Loans Status for Grade G

Grade G				
	Term: 36 Months		Term: 60 Months	
Loan Status	**Frequency**	**Percent**	**Frequency**	**Percent**
Charged Off	252	24.23%	1,796	26.32%
Current	443	42.60%	2,678	39.24%
No Credit Policy: Charged Off	5	0.48%	14	0.21%
No Credit Policy: Fully Paid	10	0.96%	16	0.23%
Fully Paid	256	24.62%	1,881	27.56%
In Grace Period	19	1.83%	125	1.83%
Late (16-30 Days)	12	1.15%	48	0.70%
Late (31-120 Days)	43	4.13%	266	3.90%
Total	1,040	100%	6,824	100%

Appendix I – Values of the Market Interest Rate as 3-Month USD LIBOR

3-Month USD LIBOR							
	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Jan	0.2501 %	0.3034 %	0.5659 %	0.3026 %	0.2382 %	0.2543 %	0.6196 %
Feb	0.2505 %	0.3119 %	0.5032 %	0.2905 %	0.2352 %	0.2584 %	0.6227 %
Mar	0.2684 %	0.3084 %	0.4733 %	0.2819 %	0.2341 %	0.2683 %	0.6320 %
Apr	0.3116 %	0.2814 %	0.4668 %	0.2771 %	0.2275 %	0.2760 %	0.6328 %
May	0.4585 %	0.2607 %	0.4665 %	0.2742 %	0.2261 %	0.2795 %	0.6456 %
Jun	0.5369 %	0.2478 %	0.4656 %	0.2737 %	0.2310 %	0.2827 %	0.6516 %
Jul	0.5103 %	0.2499 %	0.4536 %	0.2676 %	0.2342 %	0.2907 %	0.6963 %
Aug	0.3626 %	0.2932 %	0.4326 %	0.2634 %	0.2347 %	0.3208 %	0.8102 %
Sep	0.2914 %	0.3502 %	0.3856 %	0.2532 %	0.2340 %	0.3311 %	0.8497 %
Oct	0.2888 %	0.4065 %	0.3305 %	0.2418 %	0.2314 %	0.3214 %	0.8787 %
Nov	0.2871 %	0.4753 %	0.3110 %	0.2383 %	0.2329 %	0.3710 %	0.9085 %
Dec	0.3027 %	0.5557 %	0.3095 %	0.2439 %	0.2446 %	0.5332 %	0.9753 %