A Theoretical Analysis of Peer-to-Peer Lending

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1. Abstract

Peer-to-peer (P2P) lending is a new form of online lending that requires no intermediary and has experienced significant growth in the past decade. This new form of lending involves a peer-to-peer platform (website) matching borrowers and investors for unsecured loans. This paper provides a simplified theoretical framework to analyze the peer-to-peer lending market. The framework focuses on the incentive decisions and informational asymmetries in the peer-to-peer market.

The simple framework outlines three different cases, which differ by number of investor and borrower types. An extension to the simple framework, in the form of risk-averse investor preferences, is then made. A simple application that examines the effect of different parameters on the framework is made to provide insight into the question of sustainability of the peer-to-peer lending model.

Analysis of the simple framework clearly identifies the incentive requirements for borrowers and investors to enter the P2P lending market, and provides a better understanding of the decision to screen borrowers by the P2P platform. Specifically, three factors are identified that are conducive to minimal screening being performed by a peer-to-peer platform: high levels of uninformed investors, high levels of bad (high-default risk) borrowers, and a low supply of credit in the traditional banking sector. The investors' expectation of borrowers' probability of default is identified as a critical parameter in P2P markets. Adhering to the proposed theory, this paper then argues that the peer-to-peer lending model will need to evolve to remain viable in the future.

2. Acknowledgements

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3. Introduction

Since the recent financial crisis, banks have become subject to new regulatory rules intended to make them safer. Among other things, requirements for banks to hold more capital were put in place to help absorb losses in the event of another crisis. To increase its capital-to-asset ratio, a bank can only do three things: raise more capital, lend and invest less, or cut costs. Banks have been doing all three of these things for the past few years, and borrowers are feeling the effects. With the traditional banking sector restricting their lending, shadow banking institutions have emerged to fill the void. Peer-to-peer lending is one such shadow banking institution that is providing funds to needy borrowers who are being shut out by the big banks. In periods where the availability of bank credit is tightened, the demand for other sources of credit increases, and what can follow is growth in industries such as peer-to-peer lending. However, whether this growth is sustainable is not yet clear. To understand what determines the stability and success of the peer-to-peer lending market, a close examination of this new lending model is necessary.

Peer-to-peer (P2P) lending consists of individuals lending money to other individuals without the use of a traditional financial intermediary. P2P lending takes place online, with borrowers applying for loans and investors funding these loans through a P2P website. Most of the loans made are small (less than $35,000), and are used for purposes such as credit card debt, car loans, or small business startups. The P2P platform uses proprietary technology to assess the creditworthiness of borrowers and to determine the corresponding interest rates to be charged. On the P2P website, borrowers list their loan requests, and retail as well as institutional investors can fund parts or the entirety of these loan requests. The P2P platform keeps the loans on their books, collects all repayments, and pursues defaulted borrowers. For their services, they charge a percentage fee of all repaid loans.

This innovative form of lending appeared on the financial landscape in 2005 when Zopa became the first online peer-to-peer lender in the U.K. In the time since, P2P lending has experienced rapid growth. Currently in the United States, the two biggest peer-to-peer lending companies (Prosper and Lending Club) experienced a combined 177% annual growth in money loaned over the past year (2013), with over $2.4 billion loaned[1]. Although this remains only a tiny fraction of the value of loans made from the traditional banking system in the US, the growth in the industry cannot be ignored.

There is a clear division between those who support this new form of online lending and those who oppose it. The supporters of peer-to-peer lending believe that it is the logical next step forward from traditional bank lending. Traditional banks have stricter capital requirements, higher governance costs, older technology, and rigid terms on their loans. Peer-to-peer lending allows investors to compare hundreds of potential financial partners at the same time, and brings the efficiency of online transactions to a lending market. The P2P industry permits borrowers who get charged very high interest rates from traditional banks (or cannot even receive a loan) to obtain funding, while also providing investors with higher returns than most other asset classes. It is, seemingly, an excellent deal for both parties.

[1] Renton, Peter. *Lend Academy.* 31 December 2013. Accessed on 4 April 2014. http://www.lendacademy.com/p2p-lenders-2013-loan-volume/

Those who are skeptical of P2P lending will point out that there is no guarantee that investors will get their money back on time or at all. Loans are unsecured, and the P2P platform does not bear any of the risk of a defaulting borrower. Furthering on this point, there are similarities between the recent issues with loan securitization and peer-to-peer lending. In both cases, those who originate the loans (traditional banks and P2P websites, respectively) have little to no 'skin in the game'. The successful governance of loans requires adequate screening and monitoring of borrowers to ensure accurate terms to the deal and to ensure these terms are followed. However, as with a bank that securitizes a portfolio of loans, P2P lenders bear little or no risk of a defaulting loan. This provides less incentive for proper screening or monitoring. The crucial credit checking process is not well defined by some peer-to-peer websites, and it is not clear how much screening of borrowers is actually performed. It is also not evident that investors understand the risks they are undertaking by funding loans through a P2P website. Due to the relative infancy of the industry, the actual average default rates of P2P loans are not well defined (as there are only a few years of loan data), adding to the uncertainty of expected returns for investors. Another worrisome trend in the P2P lending world is the lack of clarity in the description of risks to investors entering into this market. Certain platforms draw comparisons of their loan agreements to deposits. They often refer to investors in the P2P market as "savers", and compare their rates of returns to deposit rates at banks. This can cloud the views of uninformed investors, providing a false sense of security in the loans that are, in actuality, unsecured and much riskier than bank deposits.

There is little doubt of the economic potential for this new form of lending. However, the financial conditions under which it can thrive, and the key determinants of its success, remain unclear as of yet. This paper will seek to provide simple and concise answers to these questions. Next, a specific peer-to-peer lender, Lending Club, will be introduced and the details of their lending model will be described. The Lending Club will be used as the prototype P2P platform for which the theoretical work in this paper is based.

3.1 Lending Club's Business Model

I will give a quick overview of how the Lending Club operates[2]. To be eligible for Lending Club's services an individual must register on their website as a borrower or an investor. Borrowers can submit loan requests between $1000 and $35,000. All loans are originated through the website, but are funded by an FDIC-insured industrial bank called WebBank. Lending Club does not have a banking license and so they cannot issue personal loans; they need WebBank for this. When an investor funds a loan, the principal amount is transferred from the investor's account to a funding account maintained by WebBank. These proceeds are designated for the funding of the particular loan that was purchased. Borrowers' loan requests are evaluated to determine whether the prospective borrower meets minimum criteria set out by Lending Club and WebBank. These criteria include a minimum FICO score, minimum debt-to-income ratio, and a minimum 36-month credit history. If a

[2] *Lending Club.* 30 April 2013. Accessed on 1 Mar 2014.
https://www.lendingclub.com/fileDownload.action?file=Clean_As_Filed_20130430.pdf&type=docs

borrower meets these credit criteria, they are then assigned a 'score' from an algorithm developed by Lending Club. This score corresponds to a risk grade, and each risk grade corresponds to an interest rate that will be applied to that borrower member's loan. Evidently, the worse the risk grade, the higher the interest rate applied. Investors can view this information and decide which loans (or parts of loans) they would like to fund. Upon successful repayment of a loan by a borrower, Lending Club takes a service fee from the principal as well the interest paid. If a borrower fails to make all payments, Lending Club bears no responsibility. Specifically, once the maturity date has passed on a loan, investors do not receive any later payments made by the borrower. Thus, there is a conflict of interest in the sense that Lending Club keeps all payments made past loan maturity and is also responsible for collection efforts. Lending Club acknowledges this conflict of interest in their Prospectus, but states that there is a mitigating factor to this potential conflict; fewer potential lenders will have confidence to participate on their website without diligent collection efforts. All loans that are made through Lending Club have either 3 or 5-year terms.

4. Literature Review

There has not been a large amount of research done in the area of peer-to-peer lending. As it is a relatively new phenomenon, the literature is still growing. There have been both theoretical and empirical articles written on the subject, with the majority being empirical in nature. There are two areas of emphasis in the P2P literature: 1) studies on the determinants of successfully funded loan requests, and 2) studies on investor and borrower behavior. This literature review is structured such that articles in these two areas are reviewed together. However, a useful overview article on the informational asymmetries present in P2P markets is examined first.

Freedman and Jin (2008) provided an outline of the main information problems that can exist in P2P lending, using transaction data from *Prosper.com*. They identify three main information problems. Firstly, investors face additional adverse selection due to the fact that only a borrower credit grade (as opposed to the true credit score) is observed. If you think of two borrowers who have different credit scores, but are assigned the same credit *grade* by the P2P platform, the lower credit score borrower will be driven towards the P2P market more often. Secondly, due to the fact that most investors in P2P markets are amateurs in consumer lending, they may not understand the risk associated with certain borrower attributes. The authors sought to find if any of these misunderstandings exist in a systemic manner. The relationship between a specific attribute and the probability of borrower default, as well as the relationship between the specific attribute and the borrower funding probability, were determined through OLS regressions. The results showed that P2P investors correctly interpret the meaning of the important borrower attributes (ex: credit grade), but the authors did find inconsistencies for some attributes (ex: whether or not a borrower posts a photo). Thirdly, higher interest rates can mean lower actual returns because it attracts very low-quality borrowers. The authors calculated the internal rate of return (IRR) that a sophisticated investor should expect from a P2P loan. They calculated lower IRR for higher interest P2P loans, obviously attributing this to the higher risk of these loans. This paper was useful in outlining the role of information asymmetry in the P2P market, and several issues raised here are addressed in my basic model.

The following three studies addressed the question of which attributes and information determine the successful funding of P2P loans. Iyer et al. (2009) evaluated the ability of lenders in peer-to-peer markets to use borrower information to infer creditworthiness. Using data from the P2P lender *Prosper.com*, they took advantage of the fact that lenders only observe a borrower's credit "grade" (which spans a range of credit scores) instead of their true credit score (which the authors had access to). They found that lenders were able to use available "soft" (non-verified) information to infer a third of the variation in creditworthiness of borrowers within the same credit grade. This is an interesting result given that many of the investors in P2P lending lack financial expertise and training. This study indicates that there may be a secondary screening mechanism conducted *by investors* at work in peer-to-peer markets.

Weib, Pelger and Horsch (2010) also used data from *Prosper.com* to test the hypothesis that the only characteristics of borrowers that significantly impact the probability of a credit bid's successful funding are those that are *verified* by the P2P lending platform. The results of their regressions showed that, indeed, only verified information was statistically significant to funding success. These authors' findings appear to be a contradiction to the aforementioned results of Iyer *et al.* (2009). These results would indicate that screening of potential borrowers by the P2P platform plays the most important (only) role in mitigating adverse selection, as any non-verified information does not significantly affect loan funding. However, it should be noted that Iyer *et al.* (2009) do not address the statistical significance of their results, meaning that although 'soft' information may explain some variation in borrower creditworthiness, it is not necessarily shown to be statistically significant.

A third, and final, study that examined the determinants of success in P2P lending communities was done by Herzenstein *et al.* (2008). This study first proposed a conceptual framework that works as follows in the P2P market: there are loan decision variables (loan amount, interest rate, loan duration) that act as mediators between borrower attributes and the likelihood of funding success. Borrower attributes could be anything provided by the P2P platform or the borrower to aid the investor in making their funding decision. As in the two previous studies, it is quite easy to determine whether borrower attributes significantly affect funding success, but this study adds in potential mediators of these attributes' effects. This would appear to give a more accurate picture of the true impact of a given borrower attribute on successful loan funding. The results of the authors' study showed support for their proposed conceptual framework. They found that demographic attributes (race, gender) were not statistically significant, while borrowers' financial strength was very significant.

The following papers performed work that examined P2P investor and borrower behavior, as well as the effects of their social interactions. Lin, Prabhala, and Viswanathan (2011) conducted a study on the impact of friendship networks in P2P lending. In an empirical study that used loan data from *Prosper.com* it was found that the online friendships of borrowers could act as significant signals of credit quality. The authors found that borrower friendships increase the probability of successful loan funding, lower the interest on these loans, and are correlated with lower ex-post default rates. These findings underline the role of 'soft' information in credit markets. When financial markets undergo disintermediation, a concern is the loss of 'soft' information produced by traditional intermediaries could affect credit flows. These results suggest that this concern could be mitigated to a degree with new sources producing 'soft' information (i.e. social friendship networks).

Lee and Lee (2012) conducted an empirical investigation on the presence of herding behavior in online P2P lending. Herding behavior is characterized by the lack of individual decision-making, and in financial terms describes instances where investors purchase similar investments solely because many other people are purchasing these investments. The authors found strong evidence of herding behavior amongst P2P investors. These results are quite interesting. A herding strategy often occurs because certain buyers believe that other buyers are better informed than them. For example, in the stock market inexperienced investors will often follow the "experts" (analysts). However, there are very few professional investors in the P2P market, which makes it surprising that herding behavior exists. The authors postulate that perhaps the herding behavior results from a trust on the collective intelligence of the online market, but conclude that further research needs to be done in the area.

Ceyhan, Shi, and Leskovec (2011) studied the *dynamics* of bidding behavior in P2P lending markets. The authors first investigated how loan attributes (interest rate, number of bids) change over time, and the response of investor behavior to these changes. Evidence of herding behavior was again found. The authors also built a logistic regression model to predict the success of a loan request listing and the probability of repayment based on various borrower characteristics. The model is unique in the sense that it sought to determine how temporal dynamics of bidding behavior predict loan outcome, whereas other models we've seen made predictions based solely on static features of the loan request (ex: credit grade, purpose of loan). The authors qualitatively describe the predictive ability of their model being based off "how the market feels". They found that their model had 70% prediction accuracy, and when general features of loan requests were added, the prediction accuracy only increased to 72%. Through this study, the authors showed that exploring the temporal dynamics of a loan request as opposed to looking at borrower characteristics could be a better predictor of loan performance and fundability.

From the literature it is clear that informational asymmetries play a key role in peer-to-peer lending. Additionally, the literature shows that social interactions amongst borrowers and investors, as well as investor behavior may be important factors in explaining the successful funding of different loans. However, all of the reviewed literature has placed a tight focus on specific aspects of the peer-to-peer market. This paper adds to the peer-to-peer lending literature by providing a *complete* theoretical overview of the incentive decisions and information problems inherent to the peer-to-peer market. Potential determinants of the market's sustainability are also considered, a question that has been largely unaddressed in the literature.

The theoretical framework I introduce will focus on the effects of screening borrowers to reduce information asymmetries amongst borrowers, investors, and the P2P platform. The aim of this theoretical framework is to provide clarity as to what determines the success of a peer-to-peer lending market.

To my knowledge there has been no work done that provides a complete theoretical framework to analyze P2P lending. Next, my basic model will be introduced.

5. The Basic Framework

Three simple cases, differing by number of investor and borrower types, will be considered. There are certain assumptions and features of the model that remain unchanged across all cases. Firstly, the borrowers and investors are assumed to have risk-neutral preferences. Secondly, the Lending Club is risk-neutral and acts as a profit-maximizing firm. Thirdly, borrowers all apply for loans of value 1 and promise repayment of $(1 + r)$, where r is set by the Lending Club and may vary depending on the credit-worthiness of the borrower. There are only two possible outcomes at loan maturity; the full amount owed $(1 + r)$ is repaid, or the borrower defaults and nothing is repaid. Fourthly, Lending Club charges a service fee ϕ that it takes as a percentage from the interest repayments made by borrowers. It is assumed that Lending Club has no operating expenses.

5.1 Case 1: One Type of Borrower, One Type of Investor, No Screening Required

There are n identical borrowers with the same probability of default[3] $P_D \in (0,1)$ that is observable to n identical investors and to Lending Club. Lending Club must set r such that the following incentive constraints are satisfied:

<u>Borrowers:</u>

$$r \leq r_0 \quad (1)$$

[3] It is assumed that a borrower has some 'intrinsic' probability of default. That is, a borrower's probability of default does not change with other variables (ex: interest rate).

Where r_0 is the lowest interest rate a borrower can attain from a *traditional* bank.

Investors:

Risk-neutral investors require positive expected profit:

$$(1 - P_D)(1 + r(1 - \phi)) - 1 \geq 0$$

$$r \geq \frac{P_D}{(1-\phi)(1-P_D)} \quad (2)$$

To satisfy *(1)* and *(2)* Lending Club can set r^* such that,

$$\frac{P_D}{(1-\phi)(1-P_D)} \leq r^* \leq r_0 \quad (3)$$[4]

However, Lending Club is profit maximizing, and will maximize their expected profit function:

$$E[\tilde{\pi}] = n\phi(1 - P_D)r^* \quad (4)$$

By setting $r^* = r_0$.

Thus, we see that in this setting Lending Club will set the interest rate such that borrowers are receiving a rate equal to that which they could attain elsewhere. There is no adverse selection in this simple case.

[4] It is worth noting that the parameter ϕ needs restrictions on it to ensure that this inequality can hold. In other words, Lending Club cannot charge too high of a service fee or else it may be impossible to satisfy both lender and borrower constraints.

5.2 Case 2: Two Types of Borrowers, One Type of Investor, with Screening

There are now n borrowers that can be two types; proportion α are Type A with low probability of default P_A and $(1-\alpha)$ are Type B with high probability of default P_B. There are still n investors of a single type. The investors as well as the Lending Club know that there are Type A and B borrowers, but they cannot directly observe an individual borrower's type. However, Lending Club can screen a borrower at cost c to determine her type. Without screening Lending Club can only offer a single interest rate to all borrowers, as they are indistinguishable. With screening Lending Club can offer a different interest rate for each borrower type[5]. Let's look at the borrower and investor incentive constraints *without screening* first:

Borrowers:

$$Type\ A:\ \ r \leq r_{0A} \quad (5)$$

$$Type\ B:\ \ r \leq r_{0B} \quad (6)$$

Where $r_{0A} < r_{0B}$, and r_{0A}, r_{0B} are respectively the lowest interest rates type A and type B can attain from traditional banks.[6]

Investors:

$$(1-P_L)\big(1+r(1-\phi)\big)-1 \geq 0$$

[5] In this simple model screening means that all borrowers' types are exposed. Lending Club either screens all borrowers or does not screen at all.

[6] Traditional banks can distinguish between borrower types because they always screen them. But Lending Club is not screening at this point in the model.

$$r \geq r_L = \frac{P_L}{(1-\phi)(1-P_L)} \quad (7)$$

Where P_L is the probability of default expected by investors and r_L is the investors' minimum required return. We assume $P_A < P_L < P_B$ because investors know there is some mix of A and B types.

Now we make the key assumption that $r_{0A} < r_L < r_{0B}$. Clearly, *(5), (6),* and *(7)* cannot be satisfied with a single r^*. If Lending Club sets $r^* \leq r_{0A}$ it will attract both types of borrowers but no investors and make zero profits. If Lending Club sets $r_L \leq r^* \leq r_{0B}$ it will attract the investors and Type B borrowers. If Lending Club sets $r^* > r_{0B}$ no borrowers will be attracted and they will make zero profits. Therefore, to maximize profits Lending Club will set $r^* = r_{0B}$, and will have expected profits of:

$$(1-\alpha)n\phi(1-P_B)r_{0B} \quad (8)$$

Now let's look at the constraints *with screening*:

<u>Borrowers:</u>

Equations *(5)* and *(6)*.

<u>Investors:</u>

$$r \geq r_x = \frac{P_x}{(1-\phi)(1-P_x)} \quad (9)$$

$$For\ x = A, B$$

Where r_X is the minimum required rate for investors to fund a type $'x'$ borrower.

Lending Club can now offer two interest rates, r_A^* and r_B^*, to type A and type B borrowers, respectively. They can set $r_A \leq r_A^* \leq r_{0A}$ and $r_B \leq r_B^* \leq r_{0B}$[7]. To maximize profits they set $r_A^* = r_{0A}$ and $r_B^* = r_{0B}$. They will have expected profits of:

$$\alpha\phi n(1 - P_A)r_{0A} + (1 - \alpha)\phi n(1 - P_B)r_{0B} - nc \quad \textit{(10)}$$

Now we can ask should Lending Club screen? Defining $\pi_A = \phi(1 - P_A)r_{0A}$ as Lending Club's expected profits from a type A loan and $\pi_B = \phi(1 - P_B)r_{0B}$ as their expected profits from a type B loan, screening will occur if,

$$n[\alpha\pi_A + (1 - \alpha)\pi_B - c] > n(1 - \alpha)\pi_B$$

$$c < \alpha\pi_A \quad \textit{(11)}$$

That is, Lending Club will screen if the cost of screening a borrower is less than the additional expected profit from lending to a type A borrower. Notice that the higher is the proportion of Type B borrowers $(1 - \alpha)$, the less likely it is that *(11)* will be satisfied.

5.3 Case 3: Two Types of Borrowers, Two Types of Investors, with Screening

There are now *n* investors of which there are two types: naïve (N) investors and sophisticated (S) investors. There is a proportion β of N investors. These two investor types differ in their respective expectations of default probabilities associated with the loans they fund. There are still type A and B borrowers as described in *Case 2*. As in *Case 2*, screening for cost *c* by Lending Club allows the

[7] Implicitly we have assumed that $r_A \leq r_{0A}$. That is, with full information, investors' minimum required interest rate is lower than the borrowers' maximum acceptable rate.

identity of A and B borrowers to be revealed to investors and Lending Club. Without screening, N investors believe all borrowers are Type A and expect the average probability of default to be that of an A borrower, P_A. S investors know that there is some mix of A and B types, so they expect the average probability of default to be P_S such that $P_A < P_S < P_B$. The constraints *without screening* are:

Borrowers:

Equations *(5)* and *(6)*.

Investors:

$$Type\ N: \ \ r \geq r_N = \frac{P_A}{(1-\phi)(1-P_A)} \quad (12)$$

$$Type\ S: \ \ r \geq r_S = \frac{P_S}{(1-\phi)(1-P_S)} \quad (13)$$

Where r_N and r_S are the minimum required rates for N and S investors, respectively, to fund any unscreened borrower. We now assume $r_N < r_{0A} < r_S < r_{0B}$.

Lending Club cannot set a single r^* that satisfies *(5), (6), (12),* and *(13)*. They can either set $r_N \leq r^* \leq r_{0A}$ and lose all S investors but attract both borrower types, or they can set $r_S \leq r^* \leq r_{0B}$ and lose all A borrowers but attract both investor types. The profit maximizing solutions in these two scenarios will be $r^* = r_{0A}$ and $r^* = r_{0B}$, respectively. Therefore, Lending Club's expected profits will be:

$$max\{n\beta\phi(1-P_D)r_{0A}, n(1-\alpha)\phi(1-P_B)r_{0B}\} \quad (14)$$[8]

Where $P_D = \alpha P_A + (1-\alpha)P_B$ is the average *actual* rate of default of all borrowers.

Next, we'll look at the constraints *with screening*:

Borrowers:

Equations *(5)* and *(6)*.

Investors:

Equation *(9)*[9]

Lending Club can offer $r_A \leq r_A^* \leq r_{0A}$ and $r_B \leq r_B^* \leq r_{0B}$. To maximize profits they set $r_A^* = r_{0A}$ and $r_B^* = r_{0B}$, and expected profits are as in *(10)*.

Remembering the definitions $\pi_A = \phi(1-P_A)r_{0A}$ and $\pi_B = \phi(1-P_B)r_{0B}$, screening by Lending Club will occur if:

$$n[\alpha\pi_A + (1-\alpha)\pi_B - c] > max\{n\beta\phi(1-P_D)r_{0A}, n\pi_B(1-\alpha)\} \quad (15)$$

[8] For clarification: the first expression in the max function is Lending Club's expected profit when all borrower types are attracted, but only N type investors are attracted. The interest rate is r_{0A}, and the probability of default is the average of *all* borrowers. The second expression in the max function is the expected profit when only Type B borrowers are attracted but all investors are attracted. The interest rate charged is therefore r_{0B} and the probability of default is that of Type B borrowers.

[9] With screening, both N and S investors have full information and therefore have the same expectations of borrower default risk. The minimum interest rate is the same for all investors.

To make *(15)* more readily interpretable, it is useful to examine the two different ways Lending Club can set the interest rate when they are not screening. Let's first suppose without screening they set $r^* = r_{0B}$, so that all investors, but only Type B borrowers, are attracted. Equation *(15)* now becomes:

$$n[\alpha\pi_A + (1-\alpha)\pi_B - c] > \ n\pi_B(1-\alpha)$$

$$c < \alpha\pi_A \quad \textit{(16)}$$

This is the same screening condition as was derived in *Case 2*.

Now let's suppose without screening Lending Club sets $r^* = r_{0A}$, so that all borrowers, but only Type N investors, are attracted. Equation *(15)* now becomes:

$$n[\alpha\pi_A + (1-\alpha)\pi_B - c] > \ n\beta\phi(1-P_D)r_{0A}$$

$$c < \alpha\pi_A + (1-\alpha)\pi_B - \ \beta\phi(1-P_D)r_{0A} \quad \textit{(17)}$$

Here, Lending Club's incentive to screen is decreasing as the proportion of naïve investors increases. In this scenario, all borrowers are attracted to Lending Club whether or not screening occurs. Therefore, the quantity of funded loans will depend solely on which investors are attracted. Without screening, only naïve investors will accept $r^* = r_{0A}$. Therefore, the higher is the proportion of this investor type, the less additional profit Lending Club will obtain from screening and attracting the remaining Type S investors.

6. Important Results of the Basic Framework

Despite the simplifying assumptions of this proposed model, there are some very useful and insightful results that have been developed.

6.1 Fundamental Incentive Requirements

Case 1 illustrated the fundamental incentive requirements of the peer-to-peer lending model; borrowers require an interest rate that is not above a certain level, while investors require an interest rate that is not below a certain level. The borrowers require an interest rate that is at least as appealing to them as the interest rate they could obtain from a traditional bank. The investors require an interest rate at or above an interest rate level that will earn them positive expected profit. Evidently, these two incentive requirements create a range over which Lending Club can set an interest rate to successfully attract all potential borrowers and investors. However, if the investors' minimum required interest rate exceeds the borrowers' maximum accepted interest rate, then Lending Club would not have the ability to provide attractive loan terms for both parties. That is, if this occurs the peer-to-peer lending market is no longer viable. For this reason, the size of this interest rate range provides an excellent indication of the future sustainability of the P2P market; the larger the range, the greater the shift in either investor or borrower interest rate requirements needed to bring the market to the aforementioned unviable state.

6.2 The Screening Decision

With the introduction of a discrete number of borrower types in *Cases 2* and *3* of the basic framework, Lending Club's screening decision could be examined. In both cases, Lending Club could not satisfy the incentive requirements of all borrowers and investors types without screening. With screening however, all borrowers and investors' incentives could be satisfied. The decision to screen was then examined by determining Lending Club's expected profit with and without screening.

Case 2 demonstrated that, without screening, Lending Club could only attract (relatively) bad borrowers. This resulted from the assumption that the investors demanded an interest rate that was higher than the good (Type A) borrowers could obtain from traditional banks, but lower than the interest rate the bad (Type B) borrowers could obtain. Lending Club's decision to screen was shown in *(11)*. In words, if the cost of screening a borrower is less than the additional expected profit from a good (Type A) borrower, than Lending Club will screen. Importantly, the higher is the proportion of Type B borrowers $(1-\alpha)$, the less likely it is that Lending Club's incentive to screen will be satisfied. Therefore, in a P2P market where minimal to no screening is occurring, our model suggests that this could be due to high levels of bad borrowers.

Case 3 demonstrated that when there are a discrete number of investor types, who differ in their expectations of borrower default-risk, Lending Club has a tradeoff when they do not screen; if the interest rate is set too high they will lose the good borrowers, but if the interest rate is set too low they will lose the sophisticated investors. Depending on parameter values, Lending Club could prefer to set the interest rate either way (high or low). Their screening decision is shown in *(16)* and *(17)* for the 'high interest rate' and 'low interest rate' scenarios, respectively. The scenario where the interest rate is set high leads to the same screening incentive constraint as *Case 2*. The scenario where the interest rate is set low leads to a screening incentive that is a function of, among other things, the proportion of naïve investors (β). Specifically, the higher is β, the less likely it is that Lending Club will have incentive to screen. Intuitively, this result arises due to naïve investors' expectation that all borrowers are good (Type A); no screening on the part of Lending Club is required to attract these investors. Therefore, our model has now given us another potential reason for why minimal to no screening would occur in a P2P market: high levels of uninformed investors.

6.3 Impact of Credit Conditions

The results that have been derived in the basic framework are dependent on the assumptions made regarding the relationship between the minimum interest rates each investor type requires, and the maximum acceptable rate for each borrower type. Recall that *Case 2* assumed $r_{0A} < r_L < r_{0B}$, and *Case 3* assumed $r_N < r_{0A} < r_S < r_{0B}$.[10] These assumptions resulted in the inability by Lending Club to simultaneously satisfy all investor and borrower types without screening. It is important to consider what factors could affect the relationship between these 'cut-off' interest rates. One such factor is current credit conditions in financial markets.

[10] Each of these interest rates was specifically defined in Cases 2 and 3. Revisit the section if a reminder of their definitions is required.

Credit conditions in the traditional banking sector are important to the P2P market because they affect the maximum acceptable interest rate by borrowers. The higher is the supply of credit from traditional banks the lower is the interest rate that borrowers can obtain from them. This will impact the peer-to-peer lending market. To examine this impact, let's use the *Case 2* assumptions of one investor type and two borrower types. Suppose first financial conditions are such that it is difficult to obtain credit, and so traditional banks are charging higher interest rates to borrowers. This could result in both Type A and Type B borrowers' outside attainable rates being higher than the investors' required interest rate without screening (i.e. $r_L < r_{0A} < r_{0B}$). If this occurs, all borrowers and investors can be attracted without screening (set $r_L < r^* < r_{0A}$). Conversely, if we suppose credit is in high supply from traditional banks, this could result in the investors' required interest rate being greater than the interest rates both borrower types can obtain from traditional banks (i.e. $r_{0A} < r_{0B} < r_L$). If this occurs, we have an unviable P2P loan market in the sense described in Section 6.1. Although both of the previously described examples are extreme cases[11], they effectively illustrate the potential impact of credit conditions on the P2P market.

To summarize the previous discussion, credit availability in the traditional banking sector impacts the peer-to-peer lending market through its effect on borrowers' maximum acceptable interest rate. A high supply of credit results in a lowering of this maximum interest rate, whereas a low supply of credit causes the opposite. This in turn will impact Lending Club's decision to screen; the higher the

[11]'Extreme' in the sense that the assumptions regarding r_{0A}, r_{0B}, and r_L have had the inequality relationships changed. Credit conditions could simply cause a narrowing or widening of the range between these rates without changing the inequality relationship assumed in *Case 2*.

interest rate borrowers will accept, the more likely it is that screening will not be required to attract investors[12]. Good credit conditions make it harder to attract borrowers without screening, while bad credit conditions make it easier. Therefore, our model has now provided a third reason to explain why minimal screening could be occurring in a peer-to-peer lending market; credit availability in the traditional banking sector is low.

[12] That is, the more likely it is that $r_L < r_{0A} < r_{0B}$.

7. Investor Preferences

The framework becomes slightly more complex if we assume that investors are risk-averse instead of risk-neutral. I adopt a mean-variance utility function of the form,

$$U(\widetilde{\pi}_I) = \mathrm{E}[\widetilde{\pi}_I] - \frac{\lambda}{2}\sigma^2[\widetilde{\pi}_I] \quad \textit{(18)}$$

Where investor profits, $\widetilde{\pi}_I$, is a random variable and λ is the Arrow-Pratt absolute measure of risk aversion[13].

Let's assume we are operating within the assumptions of *Case 1* of the simple model, except we have introduced risk-aversion amongst investors. The change of investor preferences alters a fundamental aspect of the basic framework: the investors' incentive constraint. To derive the new investor constraint we need to calculate the first two moments of $\widetilde{\pi}_I$. Expected investor profits and variance of investor profits for a given default probability are shown below,[14]

$$E[\widetilde{\pi}_I] = (1 - P_D)r_I - 1 \quad \textit{(19)}$$

$$\sigma^2(\widetilde{\pi}_I) = (1 - P_D)P_D r_I^2 \quad \textit{(20)}$$

Where, for ease of computation, I've defined $r_I = 1 + r\,(1 - \phi)$.

Investors require positive utility to invest, so that

$$U(\widetilde{\pi}_I) = E[\widetilde{\pi}_I] - \frac{\lambda}{2}\sigma^2(\widetilde{\pi}_I) \geq 0 \quad \textit{(21)}$$

$$(1 - P_D)r_I - 1 - \frac{\lambda}{2}(1 - P_D)P_D r_I^2 \geq 0$$

$$-\frac{\lambda}{2}(1 - P_D)P_D r_I^2 + (1 - P_D)r_I - 1 \geq 0 \quad \textit{(22)}$$

[13] See Appendix for details on the Arrow-Pratt measure.
[14] See Appendix for derivation of *(19)* and *(20).*

Solving the quadratic and substituting in for r_I yields a range for r over which investors have positive utility. The lower and upper bounds of the range are,

$$r = \frac{\left\{\frac{(1-P_D)\pm\sqrt{(1-P_D)^2-2\lambda(1-P_D)(P_D)}}{\lambda(1-P_D)(P_D)}\right\}^{-1}}{(1-\phi)} \qquad (23)^{15}$$

Given that $P_D \in (0,1)$, $\lambda \in [0,10]$, and $\phi \in (0,1)$, and that r can only take on values between 0 and 1, only the lower of the two bounds in *(23)* is relevant.[16]

Figure 1 shows how investors' expected utility as a function of r varies as their degree of risk aversion changes, holding constant other relevant parameters. *Figure 1a-c* shows the entire range of r over which investor utility is positive. *Figure 1d-e* shows investor utility over the relevant range of r (0 to 1).

The effect of changing investors' preferences from risk-neutral to risk-averse is that for a given probability of default, risk-averse investors will require a higher rate of interest than risk-neutral investors (*Figure 1d,e*). As the Arrow-Pratt measure increases, the required rate of interest increases further (*Figure 1e,f)*. This occurs because risk-averse investors derive disutility from the variance in profits. This narrows the range of r over which both the investor and borrower incentive constraints are satisfied.

[15] See Appendix for complete derivation of *(23)*.
[16] Given the range of values that P_D, ϕ, λ can take on, only the lower solution to the quadratic can fall within the allowed range for r. See Figure 1.

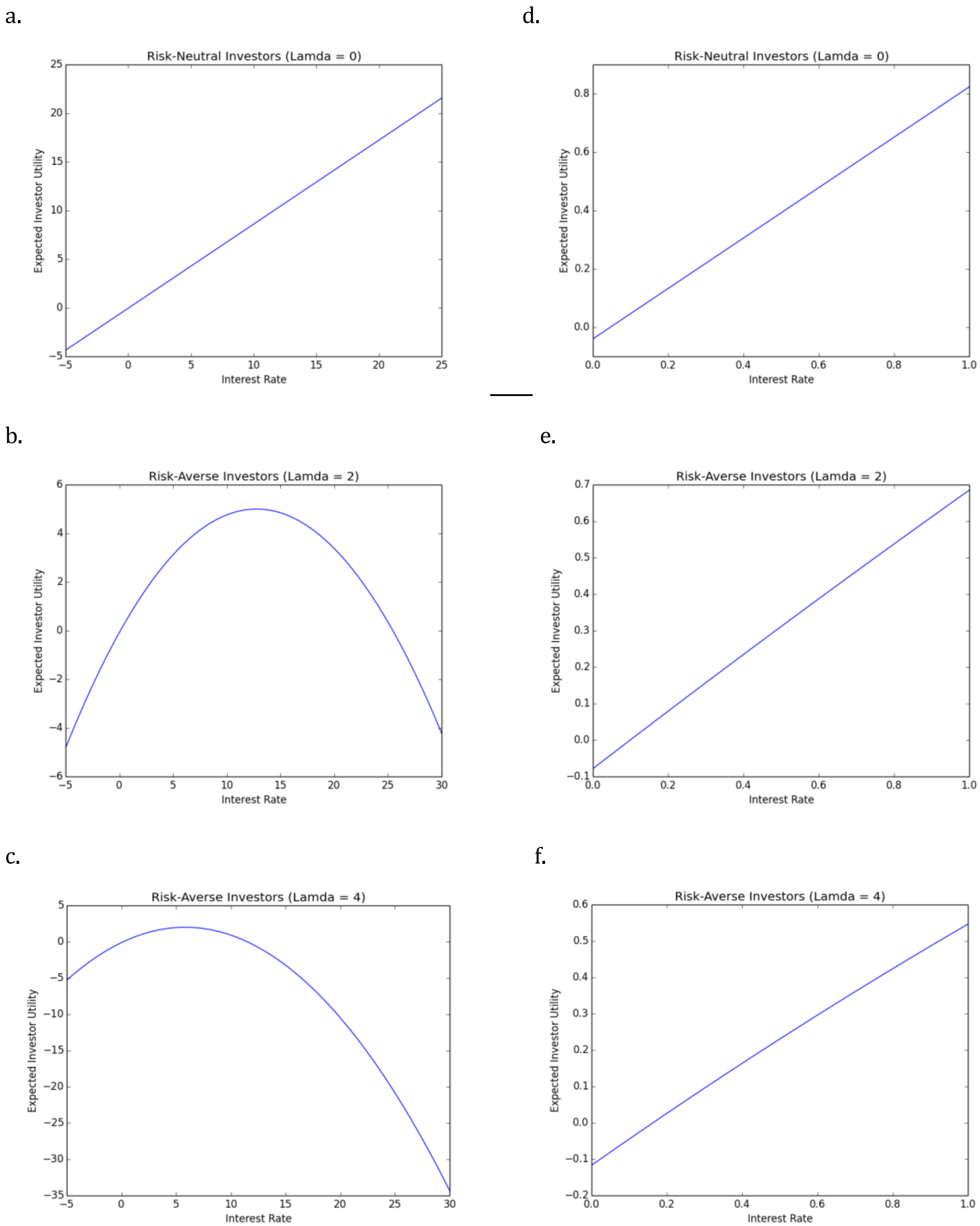

Figure 1. Expected investor utility as a function of r from funding a single loan as the Arrow-Pratt measure of investor risk-aversion (λ) varies. Other parameters are kept constant ($P_D = 0.04, \phi = 0.10$). Figure 1a-c has r varying from -5 to 30 for each λ. Figure 1d-e has r varying from 0 to 1 for each λ.

8. A Simple Application

In all the cases considered in this theoretical framework there existed a range for the interest rate set by Lending Club for which the investor and borrower incentive constraints were satisfied. The lower bound of the range was defined by the minimum interest rate that would give investors positive expected utility in funding a loan. The upper bound of the range was defined by the maximum interest rate a borrower would accept on their loan[17]. It is useful to examine how this interest rate range changes as different parameters are varied.

We will focus on the investor side of the interest rate range. The investors' minimum required interest rate is a function of three parameters: their expectation of the borrower's probability of default (P_D), Lending Club's service fee (ϕ), and the Arrow-Pratt absolute measure of risk aversion (λ). *Tables 1-3* show the investors' minimum required interest rate as each parameter is varied. The investors' minimum interest rates were calculated using *(23)*.[18]

Table 1. Investors' minimum required interest rate on a single loan as borrower probability of default varies. Other parameters are kept constant ($\lambda = 3, \phi = 0.10$).

Borrower Probability of Default	Investor Minimum Interest Rate
0.02	0.0597
0.03	0.0931
0.04	0.1294
0.05	0.1691
0.06	0.2129
0.07	0.2617
0.08	0.3168

[17]Equivalently, this was defined as the minimum interest rate a borrower could obtain on a loan from a traditional bank.
[18] Keep in mind that only the lower of the two solutions to *(23)* is used.

Table 2. Investors' minimum required interest rate on a single loan as Lending Club's percentage service fee (ϕ) varies. Other parameters are kept constant ($P_D = 0.03, \lambda = 3$).

Lending Club's Percentage Fee	Investor Minimum Interest Rate
0.00	0.0838
0.05	0.0882
0.10	0.0931
0.15	0.0986
0.20	0.1047
0.25	0.1117
0.30	0.1197

Table 3. Investors' minimum required interest rate on a single loan as the Arrow-Pratt measure of absolute risk aversion (λ) varies. Other parameters are kept constant ($P_D = 0.03, \phi = 0.10$).

Arrow-Pratt Absolute Measure of Risk Aversion	Investor Minimum Interest Rate
0	0.0344
1	0.0526
2	0.0722
3	0.0931
4	0.1156
5	0.1400
6	0.1667

There have been several simplifying assumptions made in these calculations, and the resulting calculated interest rates are not intended to be accurate. However, there is certainly important information that can be taken away from *Tables 1-3*.

It can be seen that the investors' minimum required interest rate is an increasing function of all three parameters. The investors' expectation of a borrower's probability of default has the largest effect on the investors' minimum interest rate (*Table 1*). Lending Club's service fee has minimal effect on the investors' required interest rate (*Table 2*). The investor's degree of risk aversion has a moderate affect on the investors' required interest rate (*Table 3*), but this is not a parameter that will vary much in practice.

I want to focus on the importance of the investors' expectation of a borrower's default probability. There are a few implications to consider given the large impact this parameter has been shown to have on the investors' minimum required interest rate. Firstly, if investors differ in their expectations of the borrowers' probability of default, they can have very different required minimum interest rates[19]. This brings us back to *Case 3* of the simple framework, where the effect of heterogeneous investor expectations was examined. Secondly, if investors' expectations change over time this can affect the future viability of the peer-to-peer market. In practice, it is not yet clear what the true borrower default rates are in peer-to-peer markets. If we suppose that the true default rates are higher than most current P2P investors realize, an upward shift in investors' borrower default expectations will occur in the future. This section has just shown us that the expectation of a borrower's default probability is an important parameter in determining investors' minimum required interest rate. Therefore, after their expectation adjustment, investors will require a higher interest rate, and there will be a smaller interest rate range for which both investor and borrower incentive requirements can be satisfied. If the expectation shift is large enough, we could have a scenario where investors demand a minimum interest rate that is greater than that which borrowers will accept, at which point Lending Club does not have the ability to satisfy both borrowers and investors. In other words, the P2P market would no longer be viable.

[19] Looking at *Table 1*, if two investor types differ in their borrower default expectations by just 0.01, this can result in a change in their required minimum interest rates of 0.04-0.05.

9. Conclusions

A theoretical framework has been proposed and was used to analyze the peer-to-peer lending model. This framework clearly defines the incentive requirements for investors and borrowers to enter the P2P market. Additionally, it provided three reasons as to why a P2P platform would perform minimal or no screening of borrowers; high levels of uninformed investors, high levels of bad borrowers, and difficult credit conditions. The addition of risk-averse preferences provided a realistic extension to the simple framework. In the risk-averse framework, the investors' expectation of a borrower's default probability was identified as an important parameter in determining the sustainability of a P2P market.

Currently, the peer-to-peer lending industry is experiencing rapid growth. However, the majority of peer-to-peer platforms perform minimal screening of borrowers, providing investors with little more than a 'credit grade' to form their opinions on a borrower's creditworthiness. The theory proposed in this paper has shown that if a P2P lender is not screening extensively, it may be in part due to high levels of uninformed investors, high levels of bad borrowers, or difficult credit conditions in the traditional banking sector. It is not a stretch in any sense to say that peer-to-peer markets are currently benefiting from all three of these factors.

For that reason, the growth we have recently seen in the peer-to-peer lending markets may not be sustainable. An indicator of P2P market sustainability is the size of the interest rate range that satisfies both investor and borrower incentive constraints. I argue that, in the near future, the lower bound of this range (investor's minimum requirement) will increase, and the upper bound (borrower's maximum rate) will decrease. The former argument stems from another important point emphasized in this paper; that P2P investors' expectations of a borrower's probability of default is the critical parameter in determining investors' required interest rate. This parameter will be subject to change in the future; the true default rates of borrowers are not yet well defined in P2P markets, therefore, if today's peer-to-peer lending markets have high levels of bad borrowers or high levels of uniformed investors, expectations will *have* to adjust in the coming years when these default rates are better known. This adjustment in expectations will raise the investors' required minimum interest rate. The latter argument originates from the impact of credit conditions on the P2P market. The current lack of loans being made by the traditional banking sector is helping the P2P market, as borrowers' maximum acceptable interest rate is higher than it would otherwise be in normal credit conditions. If the supply of credit from traditional banks increases in the coming years, the borrowers' maximum acceptable interest rate will be lowered. Taken together, we will have a narrowing of the feasible interest rate range. Further, if the shifts in investor and borrower requirements are large enough, the P2P lending market could reach the point where it is no longer viable.

Looking to the future, peer-to-peer markets may very well become big players in the lending industry. Under financial conditions such as the present, P2P lenders are providing a valuable service to borrowers who are having difficulty obtaining loans. However, adjustments may need to be made to ensure the sustainability of this new lending model. The informational asymmetries that exist between P2P borrowers and investors will eventually need to be lessened, most likely by improved screening, if P2P platforms want to become permanently viable lending options. This innovative lending model could potentially be a more cost-effective and efficient lending mechanism than traditional bank lending, but the industry's recent success is not definitive proof of this. Current P2P lenders may be benefiting from high levels of bad borrowers and uniformed investors, as well as favorable financial conditions, both of which will be subject to change in the near future. In the years that follow, P2P platforms may need to refine their lending model to keep satisfying their investors and borrowers. The next decade will undoubtedly be a very interesting time for the peer-to-peer lending industry.

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11. Appendices

Arrow-Pratt measure of risk aversion:

The Arrow-Pratt coefficient of absolute risk aversion λ is defined as:

$$\lambda(x) = -u''(x)/u'(x)$$

This measure increases with the curvature in the utility function.[20]

Derivation of Equations *(19)* and *(20)*:

The probability distribution of the payoff to a loan is as follows:

$$\widetilde{Payoff} = \begin{Bmatrix} r_I \; with \; probability \; (1 - P_D) \\ 0 \; with \; probability \; P_D \end{Bmatrix}$$

Where $r_I = 1 + r(1 - \phi)$

$$E\left[\widetilde{Payoff}\right] = (1 - P_D)r_I$$

$$\sigma^2\left(\widetilde{Payoff}\right) = E[Payoff^2] - E^2\left[\widetilde{Payoff}\right]$$

$$= (1 - P_D)r_I^2 - (1 - P_D)^2 r_I^2$$

$$E[\tilde{\pi}] = E\left[\widetilde{Payoff}\right] - E[1] = (1 - P_D)r_I - 1$$

$$\sigma^2(\tilde{\pi}) = \sigma^2\left(\widetilde{Payoff}\right) = (1 - P_D)P_D r_I^2$$

[20]Fabozzi, J. Frank, Edwin H. Neave, and Guofu Zhou. *Financial Economics*. United States: John Wiley & Sons, Inc., 2012. Print.

Arriving at Equation *(23)*:

We had the quadratic:

$$-\frac{\lambda}{2}(1-P_D)P_D r_I^2 + (1-P_D) - 1 \geq 0$$

Using the quadratic formula we get:

$$r_I = \frac{(1-P_D) \pm \sqrt{(1-P_D)^2 - 2\lambda(1-P_D)(P_D)}}{\lambda(1-P_D)(P_D)}$$

$$r = \frac{\left\{\frac{(1-P_D) \pm \sqrt{(1-P_D)^2 - 2\lambda(1-P_D)(P_D)}}{\lambda(1-P_D)(P_D)}\right\} - 1}{(1-\emptyset)}$$

We are interested in the r for which investor utility is positive. Given these zeroes, and a parabola that opens downwards, investor utility will be positive for all r in between the zeroes of the quadratic.