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Profile of Financial Management

What are the Determinants of lending decisions for Chinese Peer-to-Peer Lenders?

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Acknowledgement

I performed this research for my master thesis at Financial Management department of Business Administration at the University of Twente. This work focuses on determinants of lending decision for Chinese Peer-to-Peer lenders. As it is a relatively new topic in financial department, it was hard in the beginning to define the determinants, and took months to finalize this thesis.

First of all, I would like to take this opportunity to thank my first supervisor, Dr. Xiaohong Huang, for introducing me this interesting topic and her guidance and support throughout the period of thesis writing. In addition, I sincerely thank to Dr. Henry van Beusichem for being my second supervisor and his invaluable feedback and suggestions on improving the quality of this thesis.

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Abstract

Online peer to peer lending is an emerging and essential financing approach for small and micro enterprises. Over the past years, Chinese P2P lending market has developed very fast, and has become the largest market in the world. With such a rapid growth, inherent risk has also increased, especially for lenders. Prior researches summarize that P2P lenders suffer from information asymmetry, which is a fundamental and severe problem. From a lender's perspective, information asymmetry not only occurs between borrowers and lenders, but also between platforms and lenders. As a consequence, it would decrease lenders' trust on platforms/borrowers, and may lead to considerable obstacle to the development of online P2P market. To resolve it, this research aims to discover the most important determinants for Chinese lenders that influence their lending decisions; and give suggestions to borrowers and platforms on providing high-quality of information.

This research has proposed 13 hypotheses from previous studies, where 13 factors were mentioned to have impacts on lending decision. However, most of the researches were based on American context. This work validates them with an online questionnaire conducted in China, where 241 respondents were collected. Among them, 177 were willing to lend via P2P, and 64 were not willing to lend, which we analyzed with a binary logistic regression model. According to statistical analysis outcome of this model, 8 hypotheses were consistent with prior studies, while 5 were rejected. This result suggested 5 important determinants for Chinese P2P lenders; they are factors of "verified documents", "safety protection from platforms", "service quality provided by platforms", "transaction fee" and "endorsement from borrower's friend". The findings reveal that Chinese lenders' willingness to lend is affected by the quality of platforms and borrowers, rather than perceived benefit. As an indication for different parties, lenders could use the factors as a checklist to judge the quality of a loan; platforms should improve services or functions as above-mentioned to create a healthier environment for the development of P2P lending; and borrowers provide as more high-quality information (i.e. verified documents) as they can. Thus, this study provided meaningful suggestions for three parties.

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1. Introduction

Peer to peer (P2P) lending means the actions of direct lending and borrowing among private individuals occur without traditional financial institutions serving as intermediaries (M. E. Greiner & Wang, 2010). P2P lending is recognized as "a large crowd funding movement" which collects the funds from the crowd online (Burtch, Ghose, & Wattal, 2013; Zvilichovsky, Inbar, & Barzilay, 2013). Online P2P lending is an emerging and essential financing approach for small and micro enterprises (SMEs). It has been a decade since the first P2P lending platform was founded in the UK in 2005, February (Bachmann et al., 2011). With the advance of information technology and e-commerce, online P2P lending has become a supplement to traditional ways of financing, such as borrowing from banks, or borrowing from relatives and friends. P2P lending does not require the intermediary of financial institutions, whereas the platforms, such as American Prosper, British Zopa or Chinese PPDai, act as an intermediary connecting the borrowers and lenders (Bachmann et al., 2011; Galloway, 2009; Lin, 2009). Such platforms provide the opportunity for borrowers and lenders to finish transactions online without meeting in real life, and benefits can be offered for both sides. The main difference between financing via these platforms and financial institutes is that financial institutes check lenders' documents (i.e. identity, credit record, income, mortgage, etc.) in person, while P2P platforms do not have to check documents in person, and do not need mortgage. Moreover, financing via financial institutes takes longer period to receive the loan than P2P lending. In comparison, P2P lending is flexible for borrowers and lenders.

Since financing through P2P lending is more convenient with lower transaction costs than traditional financing, it has increased dramatically worldwide in countries like the United States, the United Kingdom, Japan, Canada, and China, with slightly different ways of working (Chen, Lai, & Lin, 2014). However, high risk is an inherent problem of P2P lending, and negatively affects lenders' willingness to lend. As online P2P lending develops so fast, it grabs much attention from scholars and practitioners (Bachmann et al., 2011; Galloway, 2009; Lin, 2009). In the articles of Chen and Han (2012) and Bachmann et al. (2011), they summarized and discovered from prior literatures that information asymmetry is the fundamental problem, and factors, such as credit score of a borrower, default rate, interest rate, social networking, demographic characteristics, etc., have certain impacts on mitigating such information asymmetry.

P2P lending in China grows very fast. According to Crowdfund Insider[1], the Chinese P2P lending market is the largest in the world. The main reason of its rapid growth is that the demand in Chinese market is very high, due to the fact that around half of Chinese SMEs suffer from financial restraints according to China Research Center[2]. However, there are not many researches that have been studied based on the Chinese context. Even though there are a number of researches have been studied about the American P2P lending market, they cannot be simply

[1] Crowdfund Insider, http://www.crowdfundinsider.com/2016/01/79612-report-china-p2p-lending-topped-150-billion-in-2015/

[2] China Research Center, http://www.chinacenter.net/

applied in the Chinese context due to the fact that both sides have different characteristics. For example, the credit score of borrowers is assessed by the authorized organizations in developed countries like the United States, whereas it is not applicable in China.

This paper addresses the research question: *What are the determinants of lending decisions for Chinese peer-to-peer lenders?* Thus, this research aims to discover the most important determinants for Chinese lenders that influence their lending decisions; and give suggestions to borrowers and platforms on providing high-quality of information. Hence, these determinants are not only practically helpful for three parties, but also academically be the initial step for scholars to conduct further researches in the Chinese context.

This research has contributed to a comprehensive set of validated predictors on a Chinese context, which prior studies tested them in other countries. In particular, I have collected respondents from different platforms, while prior studies only distributed questionnaire on one platform. This study discovered that the factors of “verified documents”, “safety protection from platforms”, “service quality provided by platforms”, “transaction fee”, and “endorsement from borrower’s friend” are the important determinants of lending decisions for Chinese P2P lenders. This finding reveals Chinese lenders’ decision making is affected by the quality of platforms and borrowers, rather than perceived benefit. Future P2P lending research could take these factors into consideration and compare with my result when testing for different contexts.

This research consists of 6 chapters. First a brief introduction is given. Second is about the development of P2P lending in China, and the important factors – stakeholders, loan products, lending process and transaction fee are introduced as well. Thirdly, a literature review is introduced, and thirteen hypotheses are proposed. Fourthly, the variables, online questionnaire and data analysis are introduced in the methodology chapter. In the fifth chapter, the research result is present. Lastly major findings and implications are discussed, as well as the limitations and suggestions for future research.

2. Online P2P lending in China

In this chapter, the development of Chinese P2P lending is firstly introduced. After taking a preliminary impression about Chinese P2P lending market, further questions arise: who are involved in the process, what is the lending process like, and what kind of loan products exist in the market. These questions help to have a better understanding of how it works in China. Therefore in this chapter, the important factors such as stakeholders, loan products, lending process and transaction fee are introduced.

2.1 The development of P2P lending in China

Wangdaizhijia (WDZJ), the Chinese leading and largest P2P lending guidance platform / forum, published the annual report in 2015. The report indicates that the number of P2P lending platforms has reached 2,595 by the end of 2015, which are 1,000 platforms more than the year of 2014. In 2015, the amount of lending has achieved 150 billion US dollars or 982.3 billion Chinese yuan, which is nearly four times of that in 2014. The number of borrowers and lenders also increased each year. In 2015 the number of lenders reached 5.86 million, which was 5 times of 2014. The number of borrowers was 2.85 million in 2015, which was 4.5 times of that in 2014. By comparing with the American market (see Table 1), it can be seen that the growth and development of the Chinese market is dramatic. The figures are accumulated till the end of 2015 for both countries. There are some leading, reliable and well-known platforms in China, such as PPDai.com, Dianrong, Weidai, My089 (Hongling Capital), Yooli, etc. Among them, PPDai, established in July 2007, is the first established P2P lending platform in China. By the end of 2014, PPDai has achieved nearly 4.2 million registered users included both borrowers and lenders. Another leading intermediary, my089.com, has achieved nearly 1 million users, and facilitated 18.82 billion US dollar or 122.7 billion Chinese yuan investments accumulatively since March 2009. Yet in the US, the market is dominated by two largest P2P lending platforms that are Lending Club and Prosper, with 98 percent market share[3].

	US	**China**
Total loans issued (US dollar)	25.1 billion	150 billion
Number of platforms	2	2,595
Average interest rate	15%	13.3%
First platform starting time	2006, February	2007, July

Table 1. Comparison between US and Chinese market[4] (accumulated till the end of 2015)

With such a rapid growth, however, there are some common problems that have been stated in the report as well. The number of problematic platforms increased to 896 in 2015,

[3] The Economist, March 1st 2014, Banking without banks, http://www.economist.com/news/finance-and-economics/21597932-offering-both-borrowers-and-lenders-better-deal-websites-put-two, access 9th November 2016
[4] The US figures are according to AltFi (http://www.altfi.com/article/1639_prospers_2015_in_numbers) and CrowdExpert (http://crowdexpert.com/crowdfunding-industry-statistics/).

which was nearly 3.3 times of that in 2014. WDZJ annual report of 2015[5] summarized that the problems consist of default issue, difficulty with withdraw, business cessation and economic investigations involved. Figure 1 shows the proportion of the problems. As indicated in the pie chart, high risk is an inherent problem of P2P lending. All these problems are categorized and considered as uncertainty, anonymity, lack of control, and chances for opportunism (Grabner-Kräuter & Kaluscha, 2008). So this would negatively affect lenders' willingness to lend.

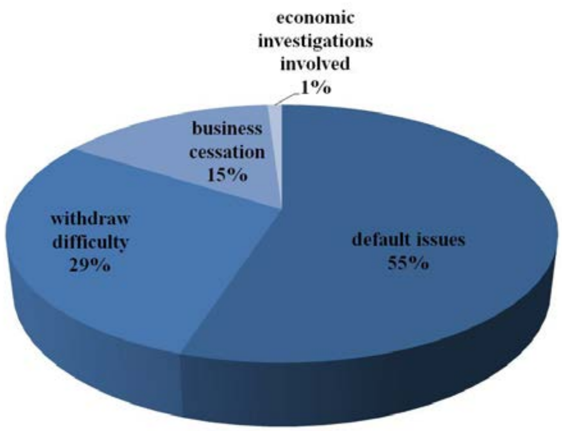

Figure 1. Types of problems of Chinese P2P platforms in 2015

2.2 Stakeholders

It is essential to identify the stakeholders who are involved in the lending process (Bachmann et al., 2011). According to Freeman's stakeholder approach, the term of stakeholder is defined as: "a stakeholder of an organization is any group or individual who can affect or is affected by the achievement of the organization's objective (Freeman, 2010, p. 276)." From this point of view, online P2P lending does not have many differences with traditional banks, which is also two-sided market (Klafft, 2008). Two-sided market is a platform that can provide various benefits for two different user groups (i.e. borrowers and lenders), especially, it can facilitate the interactions between the two groups (Rochet & Tirole, 2004). It is obvious that borrowers and lenders are the main stakeholders in the lending activities. Lenders look for opportunities to invest and maximize the profit, while borrowers aim to borrow the targeted amount of money as soon as possible with minimized costs. Not only that, lenders and borrowers in the same loan request mostly would form small communities to focus on their aims and interests (M. E. Greiner & Wang, 2009; Iyer, Khwaja, Luttmer, & Shue, 2009). The platforms, as intermediaries, are responsible to demonstrate the bid and assess the creditworthiness of the borrowers, while not responsible to recommend any loan request. Platforms also try to achieve the expectations from both sides.

In the current Chinese P2P lending market, there are two different types of lending. The

[5] WDZJ annual report of 2015 (in Chinese), http://wdzjosscdn.oss-cn-hangzhou.aliyuncs.com/nianbao/2015nianbao.pdf

roles of stakeholders, especially platforms can slightly vary. First one is the most common type, which lenders self-select and invest money to an individual borrower via the platforms, such as PPDai, Weidai, My089, etc. It involves tripartite relationships – borrowers to lenders, borrowers to platforms and lenders to platforms. However, in the second type, platforms, such as Lufax, Dianrong, CreditEase, etc., evaluate various projects, and recombine and categorize them based on the loan purposes. Then platforms distribute lenders' investments by dividing them into one category based on lenders' choice, in order to decrease the probability of default / bad loans. As for the second type, lenders are not able to assess borrowers, platforms act as borrowers more or less. Namely lenders only need to judge the creditworthiness of platforms. In this study, we only study the first type from lenders' perspective.

2.3 Loan products

There are various loan products exist in China. Basically these loan products are categorized according to the loan purposes, for instance, house loan, car loan, study loan, small and micro business loan, e-businessman loan, civil servant credit loan, etc. Or they are categorized according to the length of payback period, namely, short term loan (1 to 6 months), mid term loan (7 months to 1 year), mid to long term loan (1 to 3 years) and long term loan (longer than 3 years). Lenders are able to search and filter based on their needs. Some platforms mainly fund one particular loan product. For example, Fengtouwang, one of the first P2P platforms in China, assists lenders to fund the loans for buying second-hand cars; Daidaihong assists small business and university students to fund the loans.

2.4 Lending process

In addition to stakeholders involved in P2P lending and loan products, lending process is an important factor. The Chinese P2P lending process is quite similar to American process. For example, both American and Chinese markets have a third party involved to reduce the risk. The American third parties are more authentic financial institutions that are responsible to review the creditworthiness of borrowers. On the contrast, the Chinese third parties are often two largest online payment platforms, i.e. Alipay and Tenpay. They are responsible to temporarily store the funds and transfer back and forth between borrowers and lenders.

Before making borrowing or lending actions, every user (borrowers and lenders) needs to register an account on the platform, and have an available bank card to be able to transfer the funds and pay the transaction fees. Details about transaction fees are introduced in the next section. If borrowers apply for a loan, he / she will be required to hand in documents to show their identity and income. Additionally, the borrowers also need to propose the purpose and amount of the loan, the payback period, and interest rate[6]. When all information and documents are checked by the platform and proposal is approved, borrowers are allowed to post the loan

[6] More information about interest rate setting in China, please see appendix 2.

requests.[7] Some special loan products also require accordingly documents. For instance, civil servant credit loan requires borrowers to provide the working statements with the working numbers as civil servants; student loan requires students to provide enrolment paper and student card. With a post loan request, interested investors would review the given information to make a lending decision. The detailed process with money transferring is summarized as the following:

1. Borrowers post the loan requests on the platforms.
2. Lenders search the loan requests, evaluate the available information and make lending decision.
3. Lenders transfer money from their platform account to the third party payment platforms.
4. After funding the sufficient amount, borrowers will be paid from the third party payment platforms.
5. After a period of time, borrowers pay the capital and interest back to the third party payment platforms.
6. Then the third party payment platforms are responsible to allocate the capital and interest to each lender who has invested this loan.

This process is also shown in the following chart (Figure 2). Even though the mainstream is the same, different platforms have slight differences in lending process. For example, some platforms do not use Alipay or Tenpay as the safe way to store the funds. Instead they store the funds on their platform accounts, and let the insurance company be the assurance.

Figure 2. An example of P2P lending process in China

[7] Explanation of lending process in Chinese: http://baike.wdzj.com/doc-view-2090.html

2.5 Transaction fee

As P2P lending platforms charge a lower transaction fee and is more convenient than traditional lending approaches, this could be one of the reasons more and more people choosing this way to make investments, and making their lending decisions. For majority of P2P lending platforms, no fees are charged when posting a loan request. Fees are only charged by the platforms when lenders transfer funds to borrowers, and also when borrowers or lenders recharge money from their bank card to their platform account.

However different platforms charge the transaction fees differently, and vary in different countries as well. For instance, the transaction fees of the leading P2P lending platform in the US, Prosper.com, comprise closing fee, fines on failed payments, and late payment fees (Chen & Han, 2012). Whereas the transaction fees of PPDai consist of four types, which are service costs, cashing costs, recharging costs and late payment costs (Chen & Han, 2012). Service costs are the fees that the borrowers have to pay for all loan payments. When the loan has longer repayment period, the borrower has to pay higher service costs. Cashing costs and recharging costs are something different, which are only charged when borrowers or lenders charge and withdraw money from their accounts. On the other hand, platforms, such as My089, changjiudai, earhmony, etc., charge the VIP membership fee as well. There are quite some platforms in China that have the VIP membership system. It is quite popular, as it brings some benefits for borrowers and lenders. For example, borrowers will pay less service costs if they become the VIP member. If lenders reach higher level of VIP, the less service and transaction fees they have to pay, and the more power they have to control the interest rate setting[8]. Besides the differences of transaction fee and credit assessment between the US and China, other aspects are also summarized, see appendix 3.

[8] See appendix 2 for more information on interest rate setting.

3. Literature Review

The fundamental problem in online P2P lending, information asymmetry, is introduced. Information asymmetry can happen not only between borrowers and lenders, but also between platforms and lenders. Trust can mitigate information asymmetry for both relationships. Thus the next crucial question would be what kinds of factors lenders can use as signals to measure trustworthiness of a platform or a borrower. For lenders, the given information about borrowers and information stated on loan requests are vital signals for mitigating information asymmetry and evaluating trustworthiness. Therefore, factors that used as the vital signals are explained and categorized from three aspects – the characteristics of platforms, borrowers and loan requests in this study. Hypotheses are proposed according to these factors. At last, a conceptual framework summarizes the impact of each factor on willingness to lend.

3.1 Information asymmetry

The problem of information asymmetry is well-known in financial market (Sufi, 2007). In online P2P lending, it becomes the fundamental and severe problem between borrowers and lenders (Bachmann et al., 2011; Chen & Han, 2012; Emekter, Tu, Jirasakuldech, & Lu, 2014; Yum, Lee, & Chae, 2012). Information asymmetry happens when one party has relevant information, the other party does not have (Globerman & Vining, 1996). In this case, P2P lenders experience information asymmetry, since they are at a disadvantage (Serrano-Cinca, Gutiérrez-Nieto, & López-Palacios, 2015). The fact is that lenders want to get sufficient and reliable information about borrowers, whereas borrowers may want to hide the reality to reduce the interest rate as much as possible, and fund the target loan amount as quickly as possible (Bachmann et al., 2011). Such "imperfect information" would lead to adverse selection and moral hazard between borrowers and lenders in credit market (Bester, 1987), which is elevated in P2P lending (Lin, Prabhala, & Viswanathan, 2013). "*Adverse selection occurs when borrowers differ with respect to the probability of repaying their loan* (Bester, 1987, p. 887)". Moral hazard happens when borrowers take advantage of benefit (i.e. high interest rate) to induce lenders (Bester, 1987), while not able to payback. This may lead to high probability of default. Spence (1973) argued that both problems could be alleviated by providing high quality of signals. Mapping in P2P lending setting, good friendship or group membership, for instance, can be treated as high quality signal, in the end, such adverse selection and moral hazard could be elevated (Everett, 2015; Lin et al., 2013).

There are two reasons that information asymmetry is more severe in P2P lending than traditional financing. Firstly lenders are not close friends with borrowers. In China borrowing from friends and relatives is very common. If lenders are close friends with borrowers, they are more likely to select the right borrowers, and are able to force the borrowers to repay the loan (Berger & Gleisner, 2007, 2009). Secondly lenders are like banks that can check all the required documents in person and use analytical tools (Lin et al., 2013). Such information asymmetry can be mitigated by regular checking in person, while it is hard to detect with an anonymous way of financing on an online basis (Emekter et al., 2014). Thus lenders need to judge the trustworthiness of a borrower based on the information that is available to them. That is why information asymmetry is the springhead of these problems, and how to mitigate it becomes a crucial topic.

In China, information asymmetry not only exists between borrowers and lenders, but also exists between platforms and their users[9]. As the intermediaries, the platforms "often-cite" the successful examples, and advertise low risk of default (Yum et al., 2012). This may mislead lenders to make right decisions, and come about information asymmetry between platforms and lenders. According to the analysis between Chinese and American P2P lending markets by Sohu Stock analysis[10], the regulations and credit assessment systems are well developed in the US. About 98 percent of the US P2P lending market is dominated by two largest platforms, Prosper and Lending Club. However in China, to start and operate a P2P lending platform is relatively loose, thus it results in the current status that nearly 2,600 platforms operate in the market at the same time by the end of 2015. The reason is that in China P2P lending is an emerging industry, and the market and regulations are not very well developed. In the light of WDZJ's annual report, in China the problem of platform default often happens, and in 2015 about 900 problematic platforms were closed down. In consequence, it would decrease lenders' trust on platforms / borrowers, and may lead to considerable obstacle to the development of online P2P market (Lin, Prabhala, & Viswanathan, 2009).

3.2 Role of trust in P2P lending

Trust is specifically important when certain markets are not very efficient, just like P2P lending in China that suffering severe problems like information asymmetry (Liu, Brass, Lu, & Chen, 2015; Spence, 2002). Scholars have found that trust can mitigate such information asymmetry in e-commerce setting (Ba & Pavlou, 2002; Emekter et al., 2014). Pavlou (2003) and Chen et al. (2014) also emphasized that trust plays an important role in online lending. The reason is that it enables lenders to overcome the panic of doubt and risk which involved in loan transactions (Pavlou, 2003), and it could also affect lenders to make lending decisions (Chen et al., 2014).

Since the process of online P2P lending not only involves borrowers and lenders, but also intermediaries / platforms, trust in borrowers and trust in platforms have to be taken into consideration (Chen et al., 2014). Trust in borrowers means how confident a lender is to a borrower who will bring benefit to him / her (McKnight, Choudhury, & Kacmar, 2002). Trust in platforms refers to *"a lender believes that the intermediary will institute and enforce fair rules, procedures and outcomes in its marketplace competently, reliably and with integrity"*(Chen et al., 2014, p. 244; Pavlou & Gefen, 2004). Yet the research result of Chen et al. (2014) shows that in China trust in borrowers plays more crucial role than trust in platforms, because lenders' willingness to lend can be influenced more effectively by trust in borrowers. Wan, Chen, and Shi

[9] As mentioned, this study concentrates on the determinants of lending decisions from lenders' perspective, so this "platforms and users" relationship specifically refers to "platforms and lenders" relationship.
[10] Sohu Stock, http://stock.sohu.com/20140929/n404749996.shtml

(2016) also concluded that in China the lenders' initial trust on borrowers and perceived benefits decide the willingness to lend. Thus the next crucial question would be what kinds of factors lenders can use to measure the trustworthiness of a platform or a borrower.

3.3 Factors mitigating information asymmetry

Scholars have found some factors that can mitigate information asymmetry and help lenders to judge the loan requests when they make lending decisions. In the literature review of Chen and Han (2012), they emphasized that most of studies focused on factors that mitigate information asymmetry between borrowers and lenders, and they categorized these factors as hard credit information and soft credit information. Furthermore, Bachmann et al. (2011) also reviewed prior articles, and distinguished the hard factors and soft factors as the determinants in P2P lending. Both literature reviews have categorized that hard and soft factors can mitigate information asymmetry, while they have different understandings on what hard and soft factors are. The different ways of understanding between both articles are shown below.

		Hard factor is:	Soft factor is:
Chen and Han (2012)	Explanation / characteristics	*"credit information that can be accurately quantified, easily stored and efficiently transmitted."*	*"information that is fuzzy and hard-to quantify about borrowers "*
	Examples	1. Credit score 2. Debit to income ratio 3. Demographic information 4. Interest rate 5. Default rate	1. Social networks
Bachmann et al. (2011)	Explanation / characteristics	Financial characteristics	Non financial characteristics
	Examples	1. Credit score rating 2. Debit to income ratio 3. Default rate 4. Interest rate	1. Social networks 2. Demographic information 3. Photos / appearance

Table 2. Different understandings about hard and soft factors between Chen and Han (2012) and Bachmann et al. (2011)

Iyer et al. (2009) indicated that hard and soft factors are very important information for lenders, because by reviewing them, lenders can evaluate one third of the credit risk. Except all these, scholars have made some suggestions on mitigating information asymmetry based on hard factors and soft factors (Bikhchandani & Sharma, 2000; M. E. Greiner & Wang, 2010; Lin et al., 2013; Liu et al., 2015; Sufi, 2007). For example, social networks, as a new source of soft factor, are able to alleviate adverse selection (Lin et al., 2013). The study of Chen and Han (2012) made the comparison between the US and Chinese P2P lending markets. It has indicated that lenders from both countries are affected by hard and soft factors, while Chinese lenders rely more on soft factors for making lending decision. The reason is that Chinese market is not very well developed; and evaluating the credit score precisely is not possible. Figure 3 gives an impression on how it demonstrates the loan request and borrower's demographic information.

Although articles of Chen and Han (2012) and Bachmann et al. (2011) have different perspectives on defining the characteristics of hard and soft factors, both of them have discussed factors like credit score, default rate, interest rate, demographic characteristics and social networks. Therefore, in this study, these factors are used to hypothesize according to the Chinese market. To allow lenders making informed decisions, borrowers are often forced by platforms to provide validated documents / information, such as identity card (with demographic information), income statement, etc.; and non-validated information, such as friendship, hobbies, etc., as they have crucial impact on lending success, and perhaps on interest rate setting (Bachmann et al., 2011).

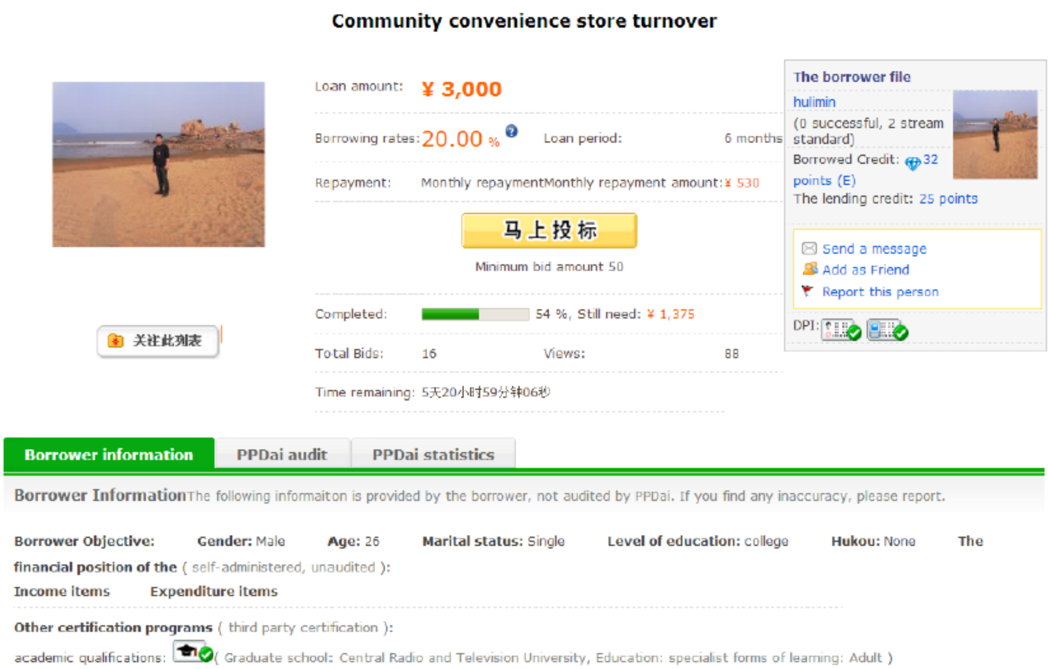

Figure 3. An example of loan Request from PPDai (translated by Google translate)[11]

3.4 Hypothesis development

From previous literature review, we now know that to make lending decision can decompose in two actions – first lenders have to choose a platform, which they can trust enough to finish online transaction; second lenders have to judge the information about the borrower that is shown on the loan request. Lin (2009) and Collier and Hampshire (2010) concluded that information about

[11] Because of the misleading translation, borrowing rate is annual interest rate. For example, in this case, lending period is 6 months, then the semi-annual interest rate is 10%. If I invest 1,000 yuan, I will receive 1,100 yuan after 6 months.

borrowers and information stated on loan requests are crucial signals to evaluate borrower's trustworthiness. Therefore, the hypotheses are proposed from three aspects – the characteristics of platforms, borrowers and loan requests.

Despite the fact that there are relationships of one factor to another, for instance, the higher credit score a borrower has, the lower probability he / she would default (Kumar, 2007; Serrano-Cinca et al., 2015). Borrowers with higher credit score have relatively more power to impact interest rate setting (Iyer et al., 2009; Klafft, 2008). Interest rate also has the association with default rate, the higher the interest rate, the higher the expected probability of default (Serrano-Cinca et al., 2015). However, this study concentrates on the determinants which affect lenders' decision making, instead of above-mentioned relationships.

3.4.1 Characteristics of platforms

Transaction fee

As mentioned in the section of transaction fee, we know that P2P lending platforms charge lower transaction fee than traditional lending approaches, which is one of the advantages of P2P lending (Bachmann et al., 2011). Low transaction fee could also be one of the reasons that more and more people choosing this way to make investments, and making their lending decisions. In P2P lending setting, it is not yet proven that low transaction fee a platform charges stimulates lenders' willingness to lend. However, online intermediaries with lower transaction fee attract more registrations, and people try to operate their business activities on the intermediaries with lower transaction fee (Jullien, 2005). Thus transaction fee is important for online context, and it is assumed to have certain effect on lenders' willingness to lend. The hypothesis is proposed below.

Hypothesis 1. Transaction fee of a platform affects lenders' willingness to lend.

Service and safety of platform

As aforementioned information, in China there are around 2,600 platforms operating in the market. Under the circumstance, it becomes challenging and essential for Chinese lenders to firstly select a reliable and trustworthy platform. According to Chen et al. (2014), service quality and safety protection have positive impact for lenders to choose platforms. It is due to that high service quality of a platform increases lenders' confidence in its reliability, capability and integrity (Eisingerich & Bell, 2007); and safety protection is able to increase trust for high risk activities, such as mobile payment and online purchasing (C. Kim, Tao, Shin, & Kim, 2010; D. J. Kim, Ferrin, & Rao, 2008).

In P2P lending context, service quality refers to "*the quality of functions and supportive activities provided by the intermediary to make the P2P lending experience more smooth and pleasant*" (Chen et al., 2014, p. 245). In order to test it, the characteristics to measure service quality are that platforms can 1) guarantee borrowers' quality, 2) provide reliable service, and 3) provide service and support during payback period (Watson, Pitt, & Kavan, 1998; Yin, 2009). Safety protection refers to "*lenders' perceptions that a lending intermediary will fulfill security requirements, such as authentication, integrity, encryption, and non repudiation*" (Chen et al., 2014, p. 245). And the characteristics to measure safety protection are 1) sufficient security means to protect users, 2) transactional information to be protected from being destroyed or altered during a transmission on the internet, 3) feeling safe to make transaction (D. J. Kim et al., 2008; Watson et al., 1998). Therefore, hypotheses are proposed accordingly.

Hypothesis 2a. Service quality of a platform affects lenders' willingness to lend.
Hypothesis 2b. Safety protection of a platform affects lenders' willingness to lend.

3.4.2 Characteristics of borrowers

Credit score

Lin (2009) found that credit score has positive association with the possibility of loan success. Yum et al. (2012) discovered that high FICO score shows high credit in P2P lending in the US[12]. Unlike credit assessment in the US, in China there is no third external agency that can validate borrower's FICO score. Therefore, Chinese lenders have to evaluate borrower's creditworthiness via other means that are available to them.

Herzenstein, Sonenshein, and Dholakia (2011) found that more information that a borrower claims on the loan request will bring about more creditworthy impression to the lenders, and in the end have more possibility to loan success. In the online microfinance setting verified documents of borrowers has positive association with loan success (M. Greiner & Wang, 2007; Yum et al., 2012). In the article of Yum et al. (2012), certificates of identification, cohabitation, income, and credit were used to measure the effect of verified documents, and they were found to have significant effect. Besides the number of information and verified information, the accumulation of borrower's transaction and repayment history is considered as creditworthiness inference that may influence lenders' decision making (Yum et al., 2012). To sum up, credit score could be assessed by evaluating verified documents and accumulation of borrower's transaction and repayment history, and the verified documents are being measured by certificates of identification, cohabitation, income, and credit. It is hypothesized as below.

Hypothesis 3a. Verified documents from a borrower affect lenders' willingness to lend.

Hypothesis 3b. The accumulated transaction and repayment history of a borrower affect lenders' willingness to lend.

Social networks

Social networks / friendships are considered to have critical impact on moderating information

[12] More information on the differences of credit assessment between two countries, please see appendix 1.

asymmetry, and lenders' willingness to lend (Chen Dongyu, 2013). In the research of Liu et al. (2015), three social relationship effects, that are considered to affect lenders' willingness to lend, were studied based on the Chinese context. The research result shows that the **pipe effect** could affect lending decisions positively, since friends are more likely to lend than strangers. This effect shows that offline closed friends have much higher willingness to lend than offline not so closed friends or online friends.

The second effect, **prism effect,** affects negatively on lending decisions (Liu et al., 2015). *Prism* is a metaphorical term, which describes the endorsements within the social network enable to provide creditable and reliable impression to the third party (Podolny, 2001). Since this argument did not mention whether on an online or offline background, both studies have opposite conclusions. The result of Liu et al. (2015) revealed that the endorsements from borrowers' friends have a negative effect on attracting third-party / potential lenders, when those third-party lenders are strangers to borrowers and their friends / endorsers. As in China, a lot of P2P lending platforms offer forums as well; friends can post endorsements for their friends and communicate with each other.

The third effect is associated with **relational herding effect**, which has positive effect on making lending decisions (Liu et al., 2015). "Herding" is known as a phenomenon, which means when lenders face obstacles of making economic decisions, they will most likely follow other people's action (Bikhchandani, Hirshleifer, & Welch, 1992; Bikhchandani & Sharma, 2000). Liu et al. (2015) have extended the concept of "relational herding" a bit, thus the conclusion in P2P lending context is that people are more likely to follow the "wisdom of crowd", especially the crowds include their offline friends. The red square in Figure 4 demonstrates the friends' bids. M. E. Greiner and Wang (2009) have concluded the more social networks a borrower has, the more possibility he / she can fund the loan successfully. Yum et al. (2012) also drew a similar conclusion – the number of friends a borrower has and the actual number of friends who bid on a loan have positive association with the possibility of successful loan funding. Therefore, it is believed that the more friends bidding the loan request, the more it will stimulate other lenders' willingness to lend. According to the above conclusion, it is hypothesized as followed.

ers	The current annual interest rate	Tender amount	Effective amount of	Status	Tender time
)57271	20.00%	¥ 500.00	¥ 500.00	✓	2012/6/26 17:35:10
vky	20.00%	¥ 140.00	¥ 140.00	✓	2012/6/26 17:38:35
36	20.00%	¥ 60.00	¥ 60.00	✓	2012/6/26 17:41:55
mao1985	20.00%	¥ 50.00	¥ 50.00	✓	2012/6/26 17:47:31
:yuk	20.00%	¥ 200.00	¥ 200.00	✓	2012/6/26 17:49:38
j2007	20.00%	¥ 500.00	¥ 500.00	✓	2012/6/26 17:51:33
zhao	20.00%	¥ 50.00	¥ 50.00	✓	2012/6/26 17:52:17

Figure 4. An example of friends' bid on PPDai (borrower's friends marked in red square)

Hypothesis 4a. The endorsement of a borrower's friend affects lenders' willingness to lend, when borrowers and endorsers are strangers to the lender.

Hypothesis 4b. The number of friends bidding for the same loan request affects lenders' willingness to lend.

Demographic information

In addition to all the above factors, demographic characteristic is also considered as the important factor for lenders to make lending decisions (Bachmann et al., 2011; Chen & Han, 2012; Herzenstein, Andrews, Dholakia, & Lyandres, 2008); whereas Ashta and Assadi (2009), Berger and Gleisner (2007) and Kumar (2007) found that borrowers' demographic characteristics may influence on lending success. It can be seen that the influence of demographic information is disputed among scholars. Since demographic characteristics which have been tested for P2P lending consist of age, gender, race, living of residence, appearance, etc. (Ashta & Assadi, 2009; Berger & Gleisner, 2007; Duarte, Siegel, & Young, 2012; Kumar, 2007), some of them have less impact on lenders' decision than the others.

Pope and Sydnor (2011) discovered borrower's age has very small impact on lenders' willingness to lend – younger borrowers, specifically younger than 35 years old, have slightly more possibilities on funding success than older borrowers (older than 60) as a matter of discrimination. However, age might have bigger influence in China, to test it, the hypothesis is made. Besides age, borrower's appearance has very important impact on lending success; the one who appears trustworthy has more likelihood to fund the loan successfully (Duarte et al., 2012). Indeed the one who appears more trustworthy has high credit score (Duarte et al., 2012). Even though uploading personal photograph is not obligated in China (most people just upload random profile pictures), it may be helpful to test its impact so that platforms can decide whether to add this obligation or not. Thus the hypothesis is made about it.

The resemblance between borrowers and lenders has strong positive influence to lenders on making lending decision. Herzenstein et al. (2008) concluded that some particular groups of people feel more congenial. The study result of Ravina (2007), which was based on the American context, indicates that when lenders find the borrowers coming from the same hometown, living in the same city, belonging to the same ethnicity and gender, lenders will have more likelihood to lend. This means these resemblances would stimulate lenders' intention to lend. Thus to test if this statement is applicable in China, the hypothesis is made.

Hypothesis 5a. Age of borrowers affects lenders' willingness to lend.

Hypothesis 5b. Borrowers who appear trustworthy affect lenders' willingness to lend.

Hypothesis 5c. Geographic resemblance affects lenders' willingness to lend.

3.4.3 Characteristics of loan requests

<u>Default rate</u>

Default refers to *"the failure to meet the legal obligations (or conditions) of a loan"*, and it has negative impact on loan success. (Sullivan, 2003, p. 261). In P2P lending setting, it happens when borrowers fail to repay to the lenders within the promised period. As previously mentioned, in China, default is the most severe problem, thus how to detect the risk of default is very important for lenders to make lending decisions. Default rate is hard to estimate in online P2P lending; hence lenders need to refer other factors to justify the risk of default.

Potential lenders usually refer borrower's yearly income and housing status (owning a house) as the significant determinants of justifying the default of a borrower (Serrano-Cinca et al., 2015). Yearly income has negatively association with default rate; so does owning a house (Serrano-Cinca et al., 2015). Mild, Waitz, and Wöckl (2015) have also discovered that repayment period, and certified securities (i.e. real estate) are the important determinants for detecting default risk. Repayment period has negative effect on default rate, thus the longer repayment period stimulates lenders' willingness to lend (Mild et al., 2015). Moreover, Kumar (2007) indicated amount of loan has positive association with default rate. The information of yearly income and the certificate of owning a house are not always provided on the loan request. To sum up, the risk of default could be detected by 1) repayment period, and 2) loan amount. Default rate should be an attribute of borrowers; however the reason to categorize it in the attribute of loan request is because the factors we use to detect it are information of loan request. Therefore, it is hypothesized as below.

<u>Hypothesis 6a. Loan amount affects lenders' willingness to lend.</u>

<u>Hypothesis 6b. Repayment period affects lenders' willingness to lend.</u>

<u>Interest rate</u>

Interest rate is another important factor which can influence lenders' willingness to lend. Higher interest rate has more likelihood to funding success and motivate lenders making lending decision (Feng, Fan, & Yoon, 2015). Borrowers with higher credit score are more capable to set lower interest rate[13] (Iyer et al., 2009). Therefore, this is the dilemma for lenders, whether they prefer to choose more benefit with higher risk, or lower benefit but more safety. However it might be not a problem for Chinese lenders, since Wan et al. (2016) found that lenders' decision making is affected by the perceived benefits, rather than perceived risk. Thus higher interest rate seems more attractive for Chinese lenders who aim to perceive higher benefit. To take a closer look at the data source of Wan et al. (2016), it is seemed to be a bit biased, since there were 86% of the participants were male. According to Barasinska (2009), male lenders would more likely choose the riskier loans than female lenders. Thus this statement should be re-tested, and the

[13] More information about interest rate setting, please see appendix 2.

hypothesis is proposed.

Hypothesis 7. Interest rate affects lenders' willingness to lend.

3.5 Conceptual framework

To summarize the hypotheses, they are categorized into three groups – attributes of platforms, Attributes of borrowers, and attributes of loan requests. According to the hypotheses, the following conceptual framework is constructed. It gives a clear picture to the relationship among independent variables (verified information, transaction and repayment history, repayment period, etc.) which lead to the independent variable (impacts of willingness to lend). As mentioned before, credit score, social networks, demographic characteristics and default rate are not easily measured by one variable. Therefore, based on the prior literature and information provided on loan requests, each of them has been decomposed into two or three variables.

	Independent variables
Characteristics of **platforms**	H1. Transaction fee
	H2a. Service quality
	H2b. Safety protection
Characteristics of **borrowers**	H3a. Verified documents
	H3b. Accumulated transaction and repayment history
	H4a. Endorsements of borrowers' friends (when borrowers and endorsers are strangers to the lender)
	H4b. Number of friends bidding
	H5a. Age of a borrower
	H5b. Appearance of a borrower
	H5c. Geographic resemblance
Characteristics of **loan requests**	H6a. Loan amount
	H6b. Repayment period
	H7. Interest rate

Table 3. Three categories of independent variables

4. Methodology

In this chapter, three subparts of methods is introduced to answer the research question: *what are the determinants of lending decisions for Chinese P2P lenders*. Firstly variables to test hypotheses are adapted or introduced in a context for Chinese P2P lending. Secondly, online questionnaire that measures the effects of these variables are explained; lastly data analysis are introduced.

4.1 Variables

In this study, it is obvious that lenders' willingness to lend is the dependent variable (willing to lend = 1, not willing to lend = 0). Thirteen independent variables are empirically tested, as they were disclosed to have crucial impact on lending success (Chen et al., 2014; Duarte et al., 2012; M. E. Greiner & Wang, 2009; Kumar, 2007; Liu et al., 2015; Mild et al., 2015; Pope & Sydnor, 2011; Ravina, 2007; Wan et al., 2016; Yum et al., 2012). Out of the 13 independent variables, three (service quality, safety protection and verified documents) cannot be directly used to measure the effects. Each of them needs 3 or 4 measurement items to test the impact on lenders' willingness to lend. Specifically, to measure the relationship between verified documents and willingness to lend, 4 measurement items are needed, which are certificate of identification, cohabitation, income and credit (Yum et al., 2012). The same goes for service quality and safety protection, as each of them needs 3 measurement items respectively.

According to the attributes of these variables, they are categorized in two groups, which are about either platform or borrower. Following table summarizes all the variables and factors that are tested for this study. The blanks in the column of measurement items mean the corresponding independent variable can be directly used to measure the effects.

	Independent variables	Measurement items
Characteristics of **platforms**	1. Transaction fee	
	2a. Service quality	Guarantee borrowers' quality
		Provide reliable service
		Provide service and support during payback period
	2b. Safety protection	Sufficient security means to protect users
		Transactional information to be protected from being destroyed or altered during a transmission on the internet
		Feeling safe to make transaction
Characteristics of **borrowers**	3a. Verified documents	Certificate of identification
		Certificate of cohabitation
		Certificate of income
		Certificate of credit
	3b. Accumulated transaction and repayment history	

	4a. Endorsements of borrowers' friends (when borrowers and endorsers are strangers to the lender)	
	4b. The number of borrower's friends joined the same bidding	
	5a. Age of borrowers	
	5b. Trustworthy appearance	
	5c. Geographic resemblance	
Characteristics of **loan requests**	6a. Loan amount	
	6b. Repayment period	
	7. Interest rate	

Table 4. Overview of variables and factors used to verify hypotheses

4.2 Questionnaire

Questionnaire[14], as one quantitative research approach, is appropriate for hypotheses testing. It allows collecting big amount of data, and also allows discovering what the significant determinants are to affect lenders' willingness to lend in this case. Questionnaire is formed by series of questions to gather information from respondents. In this research, the questionnaire consists of two parts. The first part is the main construct for testing the hypotheses. Totally 13 hypotheses are proposed with 20 questions in the questionnaire. It is because 3 hypotheses are proposed to have 3 or 4 measurement items in prior studies. Namely, hypothesis 2a and 2b respectively need 3 measurement items, in other words, 3 questions to test each of them. Meanwhile, hypothesis 3a needs 4 measurement items. Such independent variable is determined as the mean of these 3 or 4 relevant measurement items. Corresponding questions can be found in the following table (see Table 5). In the second part of the questionnaire, general questions are being asked, such as gender, age, and personal experience with P2P lending. The online questionnaire is designed by using likert scale, which scales from one (strongly disagree) to five (strongly agree) in order to measure how strong an independent variable affects willingness to lend. Likert scale with five response categories is the most commonly used in social science research. All the hypotheses with corresponding questions in this study are listed below.

	Questions: When I make lending decisions, my lending intention will be affected by …
<u>Hypothesis 1</u>. Transaction fee of a platform affects lenders' willingness to lend.	Low transaction fee
<u>Hypothesis 2a</u>. Service quality of a platform affects lenders' willingness to lend.	Guarantee borrowers' quality
	Provide reliable service
	Provide service and support during repayment period

[14] For online questionnaire, please go to appendix 4.

Hypothesis 2b. Safety protection of a platform affects lenders' willingness to lend.	Sufficient security means to protect users
	Transactional information to be protected from being destroyed or altered during a transmission on the internet
	Feeling safe to make transaction
Hypothesis 3a. Verified documents from a borrower affect lenders' willingness to lend.	Verified identity card from a borrower
	Verified marital status from a borrower
	Verified income from a borrower
	Verified credit from a borrower
Hypothesis 3b. The accumulated transaction and repayment history of a borrower affect lenders' willingness to lend.	Accumulated transaction and repayment history of a borrower
Hypothesis 4a. The endorsement of a borrower's friend affects lenders' willingness to lend, when borrowers and endorsers are strangers to the lender.	Endorsement of a borrower's friend (when borrowers and endorsers are strangers to the lender)
Hypothesis 4b. The number of friends bidding for the same loan request affects lenders' willingness to lend.	Many of borrower's friends joined the same bidding
Hypothesis 5a. Age of borrowers affects lenders' willingness to lend.	Young borrower (younger than 35 years old)
Hypothesis 5b. Borrowers who appear trustworthy affect lenders' willingness to lend.	Borrowers who appear trustworthy
Hypothesis 5c. Geographic resemblance affects lenders' willingness to lend.	Geographic resemblance
Hypothesis 6a. Loan amount affects lenders' willingness to lend.	High loan amount
Hypothesis 6b. Repayment period affects lenders' willingness to lend.	Long repayment period
Hypothesis 7. Interest rate affects lenders' willingness to lend.	High interest rate

Table 5. Overview of hypotheses and their corresponding questions

Prior researches used data from one single platform, which creates sampling biases. To resolve it, this study tries to collect respondents from different platforms. There is no specific requirement for selecting respondents. The questionnaire is edited on Wenjuanxing (WJX)[15], a Chinese online questionnaire editing tool, which is similar to Surveymonkey. The online questionnaire is published on four channels, which are forums of P2P platforms (i.e. PPDai, Weidai, Tuandai, Iqinjin, etc.), WDZJ (the Chinese leading and largest P2P lending guidance platform / forum), Baidu Tieba (the largest Chinese communication platform), Weibo (Chinese version of Twitter). As many platforms in China operate their own forums for users to share experiences with each other, and for themselves to publish news or promote their new services.

[15] Access of Wenjuanxing: http://www.sojump.com/

Thus forums should be an ideal place to publish the questionnaire. Any respondents can answer the questionnaire, so they are randomly selected. Before officially launching the questionnaire, pretest is useful, because it helps to screen out or rephrase any questions that do not make sense to respondents. As the size of this questionnaire is relatively small, 5 targeted respondents should be enough for pretest. By reviewing their feedback, I improved the questionnaire from three aspects. First, a brief introduction about P2P lending was added to help inexperienced respondents understand P2P lending. Second aspect was about question skip logic, as it seemed not clear to put the guide by the end of each answer, i.e. please go to Question X. Later on I discover Wenjuanxing provides the function for question skip logic, which also makes sure the corresponding respondents answer the right questions. According to the simulation study of van der Ploeg, Austin, and Steyerberg (2014), they confirmed that 10 observations per predictor is acceptable for logistic regression; and 20 to 50 observations per predictor is optimum. To get a better performance of the result, I proposed to recruit 15 observations per predictor. With 13 predictors in this study, 195 respondents are needed.

4.3 Analysis

To analyze the data, five essential approaches should be performed. Firstly, descriptive statistics are used to summarize the collected data, such as mean, standard deviation and frequencies. Since the questionnaire uses a likert scale from 1 to 5, when the mean of particular variable is greater than 3, we could preliminarily explain that majority respondents select 4 (agree) or 5 (strongly agree). Secondly, reliability testing utilized Cronbach's Alpha, which checks the consistency of a set of questions or measurements within the test. When Cronbach's Alpha is above 0.7, the internal consistency of the sample is considered to be acceptable (Georgy & Mallery, 2001). Thirdly, an overall model fit is tested by applying Nagelkerke R^2, which is the modified Pseudo R^2 reported in SPSS for measuring model fit for binary logistic regression. Its interpretation is similar to the R^2 in linear regression, which also interpret the proportion of variance in the dependent variable is explained by the independent variables. The higher the R^2 value is, the better the model fits the data. Although SPSS reported Cox & Snell R^2 as well, Cox & Snell R^2 cannot reach 1. In addition, Nagelkerke R^2 is an adjusted version of Cox & Snell R^2, which is possible to reach 1. Nagelkerke R^2 is applied for this study, since it covers all possible values. Fourthly multicollinearity is checked, since multicollinearity is a common problem in linear regression. The most widely-used for multicollinearity diagnosis is variance inflation factor (VIF). The larger the VIF is, the more probability that multicollinearity issues would be. In logistic regression, when VIF is above 2.5, researchers may need further investigations (Olague, Etzkorn, Gholston, & Quattlebaum, 2007).

Lastly, logistic regression is used to study the relationship between the dependent variable (willingness to lend) and 13 independent variables. In the questionnaire (see appendix 4), the dependent variable is designed as a binary or dichotomous variable with answers either willing to lend or not willing to lend. The independent variables are measured in a likert scale from 1 to 5.

Because of the binary dependent variable, the conventional linear regression is not appropriate. To resolve it, utilizing sigmoid function is appropriate. For example, a logistic regression model is formulated as

$$P = \frac{1}{1 + Exp(-Z)},$$

where P is the probability of willing to lend, and Z is a linear function of independent variables,

$$\begin{aligned} Z = \beta_0 &+ \beta_1 * TransFee + \beta_2 * ServiceQuality + \beta_3 * SafetyProtection \\ &+ \beta_4 * VerifiedDoc + \beta_5 * AccumTrans + \beta_6 * FriendsEndors + \beta_7 \\ &* \#FriendsBid + \beta_8 * Age + \beta_9 * Appearance + \beta_{10} * GeoResemblance \\ &+ \beta_{11} * LoanAmount + \beta_{12} * RepayPeriod + \beta_{13} * InterestRate, \end{aligned}$$

β_0 is the intercept, and $\beta_1, \ldots, \beta_{13}$ are coefficients of independent variables. By computing the logarithm of the odds$\left(\frac{P}{1-P}\right)$, we have

$$\begin{aligned} log\left(\frac{willing\ to\ lend}{not\ willing\ to\ lend}\right) &= log\left(\frac{P}{1-P}\right) \\ &= \beta_0 + \beta_1 * TransFee + \beta_2 * ServiceQuality + \beta_3 * SafetyProtection \\ &+ \beta_4 * VerifiedDoc + \beta_5 * AccumTrans + \beta_6 * FriendsEndors + \beta_7 \\ &* \#FriendsBid + \beta_8 * Age + \beta_9 * Appearance + \beta_{10} * GeoResemblance \\ &+ \beta_{11} * LoanAmount + \beta_{12} * RepayPeriod + \beta_{13} * InterestRate. \end{aligned}$$

Clearly, the link function, i.e. $log\left(\frac{P}{1-P}\right)$ (often termed as a logit function), is an increasing function with respect to P. Also, because P is in (0, 1), the function value lies in $(-\infty, +\infty)$. In addition, coefficients $\beta_1, \ldots, \beta_{13}$ can quantify the relationship of each independent variable to willingness to lend in this study. Qualitatively, a positive β indicates a positive effect. In a more quantitative way, the larger the absolute value of β, the stronger the effect. Furthermore, Exp(β) is called as the odds ratio. For one particular variable, when the independent variable X_k is increased with one unit step (e.g. from 2 to 3 on a likert scale), the odds is enhanced by an Exp(β_k) fold.

SPSS is used to perform the above statistical analysis. Since the dependent variable of logistic regression is binary, the groups, willing to lend and not willing to lend, are coded either 0 or 1. The coefficients (β), which are interpreted, reflect the impact of independent variables on the group coded as 1 (Hair, 2010). The interest of this study is people who are willing to lend, therefore, we code this group as 1, and the other (not willing to lend) group as 0.

5. Research Result

In this chapter, the research findings are presented. First the overview of respondents is indicated, and then the reliability test and overall model fit are checked. Afterwards 13 hypotheses proposed previously are testified by analyzing logistic regression model. Robustness test is conducted by checking three different groups. Lastly a summary about expected and observed relationship between dependent and each independent variable is addressed.

5.1 Process of data collection

As described in section 4.2, I planned to distribute the online questionnaire via four channels, which are forums of P2P platforms (i.e. PPDai, Weidai, Tuandai, Iqinjin, etc.), WDZJ (the Chinese leading and largest P2P lending guidance platform / forum), Baidu Tieba (the largest Chinese communication platform), Weibo (Chinese version of Twitter). Unfortunately, based on the rules and regulations of the forums, it is not allowed to post any messages that contain advertisement (i.e. posting questionnaire links). As a consequence, only 43 questionnaires were collected from social media (Baidu Tieba and Weibo), and 13 of them were screened out, as the time spending for answering the questionnaire was too short. Thus 30 valid questionnaires were collected from social media.

At the same time, WJX, the Chinese online questionnaire tool I used to design the questionnaire, provides data collection service, thus I requested WJX to recruit 200 respondents. All respondents are rewarded by a chance of lucky draw when completing the questionnaire, which is common and ethical for experiment on human beings. WJX provides quite reliable service, because the whole recruiting process is monitored, and each IP address can only answer the questionnaire once. In the end 211 valid questionnaires were collected from WJX. In total, 241 valid questionnaires were collected.

5.2 Respondents overview

Two demographic characteristics are measured – gender and age. The distributions of them are firstly present in Table 6. In this sample, gender is distributed quite evenly (54.8% male vs. 45.2% female). While age is not, 66% of respondents were young people (below 35 y.o.), and only 1 older respondent answered the questionnaire.

Items		Frequency	Percent
Gender	Male	132	54.8%
	Female	109	45.2%
Age (years old)	25 or below	23	9.5%
	26~35	136	56.4%
	36~45	59	24.5%
	46~60	22	9.1%
	Above 60	1	.4%

Table 6. Overview of respondents' characteristics (N=241)

		Experience		
		No experience	With experience	Total
Willingness	Not willing to lend	32	32	64
	Willing to lend	64	113	177
Total		96	145	241

*Table 7. Crosstabulation of willingness to lend * experience with P2P (N=241)*

Table 7 shows 177 respondents (about 73.4%) are willing to lend via P2P; whereas 64 respondents (about 26.6%) are not willing to lend. This answer is used as dependent variable for binary logistic regression analysis. The table also indicates As mentioned before, one of the differences between this study and prior P2P studies is that this study collected data from several platforms in order to minimize sample biases rather than one platform. For this reason, Table 8 summarized frequently-used platforms by only asking people who selected “with experience”. The platform of Yirendai (with 71 respondents) is relatively more frequently used by the experienced respondents, followed by PPDai (64 respondents), Hongling capital (42 respondents) and Weidai (42 respondents).

Ranking	Name of platform	Frequency
1	Yirendai	71
2	PPDai	64
3	Hongling	42
3	Weidai	42
5	Jinxin	24
6	Tuandai	23
7	Ijinqian	16
8	Guanetong	7
9	Xinhehui	7
10	Other	9

Table 8. Overview of frequently-used platforms (answered by respondents with P2P experience)

5.3 Reliability test

Before analyzing the data, reliability test should be done by checking the value of Cronbach’s Alpha. It checks the internal consistency of a set of questions or measurements within the test. As shown in Table 8, the Cronbach’s Alpha of this study is .767, which means the internal consistency is acceptable (Georgy & Mallery, 2001)[16].

Reliability statistics

N of items	Cronbach’s Alpha
13	.767

Table 9. Internal consistency of all variables

[16] According to Georgy and Mallery (2001), $\alpha \geq 0.9$ Excellent, $0.9 > \alpha \geq 0.8$ Good, $0.8 > \alpha \geq 0.7$ Acceptable, $0.7 > \alpha \geq 0.6$ Questionable, $0.6 > \alpha \geq 0.5$ Poor, $0.5 > \alpha$ Unacceptable

5.4 Overall model fit

Before analyzing logistic regression model, the overall model fit is checked. Nagelkerke R^2 is applied for such test. Its interpretation is similar to the R^2 in linear regression, which also interpret the proportion of variance in the dependent variable is explained by the independent variables. As mentioned before, Nagelkerke R^2 is applied for this study, since it covers all possible values from 0 to 1. Table 10 indicates Nagelkerke R^2 is .283, which means nearly 30 percent of variance in the dependent variable can be explained by our independent variables.

Model summary

-2 Log likelihood	Nagelkerke R Square
227.048	.283

Table 10. Overall model fit

Besides Nagelkerke R^2, classification table which produced from SPSS is helpful to check how good our model is in predicting the observed outcomes. To explain it, in Table 12, 28 observations that are not willing to lend are observed and are correctly predicted by our model; 169 observations that are willing to lend are observed and are correctly predicted by our model. The overall percentage tells us that our model is able to correctly predict 81.7 percent of the two categories. By comparing with the null model[17] in Table 11, the overall percentage increased from 73.4% to 81.7%, which means our model predicts better outcome when independent variables were plugged in.

Classification table

Observed			Predicted		
			Q6a_willingness_to_lend		Percentage Correct
			not willing to lend	willing to lend	
Step 0	Q6a_willingness_to_lend	not willing to lend	0	64	0%
		willing to lend	0	177	100%
	Overall Percentage				73.4%

Table 11. The observed and predicted frequencies in null model

Classification table

Observed			Predicted		
			Q6a_willingness_to_lend		Percentage Correct
			not willing to lend	willing to lend	
Step 1	Q6a_willingness_to_lend	not willing to lend	28	36	43.8%
		willing to lend	8	169	95.5%
	Overall Percentage				81.7%

Table 12. The observed and predicted frequencies in full model

[17] SPSS runs logistic regression in 2 steps. First step, also called step 0, shows us the null model. It includes no independent variables, but only the intercept. Normally researchers are not interested in step 0, but it is used to compare the outcomes of how the model is when independent variables are plugged in. Please check http://www.ats.ucla.edu/stat/spss/output/logistic.htm for more information.

5.5 Relationships between willingness to lend and each independent variable

After checking the reliability and goodness of fit of our model, logistic regression analysis is conducted. Since the dependent variable of logistic regression is binary, the groups, willing to lend and not willing to lend, are coded either 0 or 1. The coefficients, which are interpreted, reflect the impact of independent variables on the group coded as 1 (Hair, 2010). The interest of this study is people who are willing to lend, therefore, we code this group as 1, and the other (not willing to lend) group as 0.

5.5.1 Relationships between attributes of platforms and willingness to lend

Transaction fee

The first independent variable of this study is transaction fee. As already mentioned, even though it is not yet proven that low transaction fees that platforms charge stimulate lenders' willingness to lend, it is proven that online intermediaries with lower transaction fee attract more registrations, and people try to operate their business activities on the intermediaries with lower transaction fee (Jullien, 2005). Plus, lower transaction fee is one of the benefits of P2P lending compared with traditional financing (Chen & Han, 2012). Thus *hypothesis 1 transaction fee of a platform affects lenders' willingness to lend* is tested.

In Table 13, the mean is 3.89 with standard deviation .90. The distribution[18] of low transaction fee shows most of respondents select 4 (agree), followed by 5 (strongly agree) and 3 (neutral). To investigate the relationship between low transaction fee and willingness to lend using logistic regression, the estimated coefficient (β value in Table 14) is positive (.713). With a p-value .000, this indicates a significant relationship. Thus, hypothesis 1 is accepted. Additionally, in Table 14, the odds ratio, Exp(β), is 2.040, which could have a meaningful indication for lending platform design. For example, with some hypothetical modifications about transaction fee to a platform (i.e. lower the transaction fee, and no change for other factors), lenders have an increased score by one category (e.g. from 3 to 4 on a likert scale). The logistic model can suggest that lenders' willingness to lend is 2.040 times affected by lower transaction fee. In addition, estimates of coefficients and Exp(β) from the logistic regression help to quantitatively understand effects of single independent variable in a lending platform on the lenders' decisions.

Descriptive statistics		
	Mean	Std. Deviation
P1_LowTransactionfee	3.89	.90
P2_ServiceQuality	3.92	.84
P3_SafetyProtection	3.90	.89
B1_VerifiedDoc	3.96	.69
B2_AccumTrans	3.96	.92
B3_FriendEndores	3.46	1.03
B4_MoreFriendsbid	3.41	1.03

[18] Please see appendix 6 for distribution of each independent variable stated in bar charts.

B5_YoungBorrower	3.20	1.04
B6_TrustAppearance	2.70	1.21
B7_GeoResemblance	2.76	1.17
I1_HighLoanAmount	3.78	.83
I2_LongRepayPeriod	3.85	.95
I3_HighInterestRate	3.94	.94

Table 13. Mean and standard deviation of each predictor

Logistic regression: variables in the equation

	B	Wald	Sig.	Exp(B)
P1_LowTransactionfee	.713	17.509	.000**	2.040
P2_ServiceQuality	.911	23.048	.000**	2.487
P3_SafetyProtection	.918	25.751	.000**	2.505
B1_VerifiedDoc	1.245	27.035	.000**	3.473
B2_AccumTrans	.481	9.131	.003**	1.617
B3_FriendEndores	.496	11.687	.001**	1.643
B4_MoreFriendsbid	.463	10.113	.001**	1.589
B5_YoungBorrower	.068	.237	.626	1.071
B6_TrustAppearance	.116	.905	.341	1.123
B7_GeoResemblance	.088	.492	.483	1.092
I1_HighLoanAmount	.481	7.316	.007**	1.617
I2_LongRepayPeriod	.283	3.441	.064	1.326
I3_HighInterestRate	.031	.040	.842	1.031
Constant	-4.432	10.264	.001**	.012

Table 14. Logistic regression result (N=241)

Note: The statistical significance of each β coefficient is tested by using Wald test. ** represents *significant in 95% confidence level.*

Service quality

The second independent variable of this study is service quality a platform provides. By analyzing the logistic regression, *hypothesis 2a service quality of a platform affects lenders' willingness to lend* is tested. Since three measurement items were used to test service quality, it is necessary to test whether each of measurement items is internally consistent with service quality. In Table 15, the internal consistency is good[19], as the overall Cronbach'a alpha is .814. Since Cronbach's Alpha will be decreased if any one of them is deleted, all 3 measurement items should be retained.

Reliability statistics

N of items	Cronbach's Alpha
3	.814

	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's Alpha if item deleted

[19] According to Georgy and Mallery (2001), α ≥ 0.9 Excellent, 0.9 > α ≥ 0.8 Good, 0.8 > α ≥ 0.7 Acceptable, 0.7 > α ≥ 0.6 Questionable, 0.6 > α ≥ 0.5 Poor, 0.5 > α Unacceptable

guarantee_borrower_quality	7.92	2.518	.699	.725
reliable_service	7.78	3.053	.730	.683
service_support_during_repayment	7.79	3.582	.599	.812

Table 15. Internal consistency of service quality

In Table 13, the mean is 3.92 with standard deviation .84. The distribution of service quality shows most of respondents select 5 (strongly agree), followed by 4 (agree) and 3 (neutral). To investigate the relationship between service quality and willingness to lend using logistic regression, the estimated coefficient (β value in Table 14) is positive (.911). With a p-value .000, this indicates a significant relationship. Thus, hypothesis 2a is accepted. Additionally, in Table 14, the odds ratio, Exp(β), is 2.487. It means with some hypothetical modifications about service quality of a platform (i.e. upgrading service quality, and no change for other factors), lenders have an increased score by one category (e.g. from 3 to 4 on a likert scale). The logistic model can suggest that lenders' willingness to lend is 2.487 times affected by the upgraded service quality.

<u>Safety protection</u>

The third independent variable of this study is safety protection provided by a platform. By analyzing the logistic regression, *hypothesis 2b safety protection of a platform affects lenders' willingness to lend* is tested. Since three measurement items were used to test safety protection, it is necessary to test whether each of measurement items is internally consistent with safety protection. In Table 16, the internal consistency is good, as the overall Cronbach'a alpha is .854. Since Cronbach's Alpha will be decreased if any one of them is deleted, all 3 measurement items should be retained.

Reliability statistics

N of items	Cronbach's Alpha
3	.854

	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's Alpha if item deleted
sufficient_security_protect_users	7.76	3.223	.753	.769
trans_info_being_protected	7.80	3.549	.701	.817
feel_safe	7.83	3.497	.722	.798

Table 16. Internal consistency of safety protection

In Table 13, the mean is 3.90 with standard deviation .89. The distribution of safety protection shows most of respondents select 5 (strongly agree), followed by 4 (agree) and 3 (neutral). To investigate the relationship between independent and dependent variables using logistic regression, the estimated coefficient (β value in Table 14) is positive (.918). With a p-value .000, this indicates a significant relationship. Thus, hypothesis 2b is accepted. Second, in Table 14, the odds ratio, Exp(β), is 2.505. It means with some hypothetical modifications about safety protection of a platform (i.e. improve safety protection, and no change for other factors), lenders have an increased score by one category (e.g. from 3 to 4 on a likert scale). The logistic model can suggest that lenders' willingness to lend is 2.505 times affected by the improved safety protection.

5.5.2 Relationships between attributes of borrowers and willingness to lend

Verified documents

The fourth independent variable of this study is verified documents which are provided by a borrower. By using logistic regression, *hypothesis 3a verified documents from a borrower affect lenders' willingness to lend* is tested. Since four measurement items were used to test verified documents, internal consistency is necessary to check. In Table 17, the internal consistency is acceptable, as the overall Cronbach'a alpha is .747. Although when measurement item of verified marital status is deleted, internal consistency will be improved. It is still in the acceptable range, thus I decided to keep it for now.

Reliability statistics

N of items	Cronbach's Alpha
4	.747

	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's Alpha if item deleted
verified_identitycard	11.64	4.797	.620	.654
verified_maritalstatus	12.32	5.110	.337	.809
verified_income	11.82	4.325	.634	.635
verified_credit	11.73	4.396	.622	.643

Table 17. Internal consistency of verified documents

As indicated in Table 13, the mean is 3.96 with standard deviation .69. The distribution of verified documents shows most of respondents select 4 (agree), followed by 5 (strongly agree), and 3 (neutral). To investigate the relationship between independent and dependent variables using logistic regression, the estimated coefficient (β value in Table 14) is positive (1.245). With a p-value .000, this indicates a significant relationship. Thus, hypothesis 3a is accepted. Additionally, in Table 14, the odds ratio, Exp(β), is 3.473. It means with some hypothetical modifications about verified documents, lenders have an increased score by one category (e.g. from 3 to 4 on a likert scale). The logistic model can suggest that lenders' willingness to lend is 3.473 times affected by the verified documents.

Accumulated transaction and repayment history

The fifth independent variable of this study is accumulated transaction and repayment history of a borrower. By analyzing the logistic regression, *hypothesis 3b the accumulated transaction and repayment history of a borrower affect lenders' willingness to lend* is tested. As indicated in Table 13, the mean is 3.96 with standard deviation .92. The distribution of accumulated transaction and repayment history shows most of respondents select 4 (agree), followed by 5 (strongly agree) and 3 (neutral). To investigate the relationship between independent and dependent variables using logistic regression, the estimated coefficient (β value in Table 14) is positive (.481). With a p-value .003, this indicates a significant relationship. Thus, hypothesis 3b is accepted. Additionally, in Table 14, the odds ratio, Exp(β), is 1.617. It means with some hypothetical modifications about accumulated transaction and repayment history, lenders have an increased score by one category (e.g. from 3 to 4 on a likert scale). The logistic model can suggest that lenders' willingness to lend is 1.617 times affected.

Endorsement of borrower's friend

The sixth independent variable of this study is accumulated transaction and repayment history of a borrower. By analyzing the logistic regression, *hypothesis 4a the endorsement of a borrower's friend affects lenders' willingness to lend, when borrowers and endorsers are strangers to the lender* is tested. As indicated in Table 13, the mean is 3.46 with standard deviation 1.03. The distribution of endorsement of borrower's friend shows most of respondents select 4 (agree), followed by 3 (neutral). To investigate the relationship between independent and dependent variables using logistic regression, the estimated coefficient (β value in Table 14) is positive (.496). With a p-value .001, this indicates a significant relationship. Hypothesis 4a is accepted. Additionally, in Table 14, the odds ratio, Exp(β), is 1.643. It means with some hypothetical modifications about endorsement of borrower's friends, lenders have an increased score by one category (e.g. from 3 to 4 on a likert scale). The logistic model can suggest that lenders' willingness to lend is 1.643 times affected.

The number of friends bidding

The seventh independent variable, the number of friends bidding is being tested. By analyzing the logistic regression, *hypothesis 4b the number of friends bidding for the same loan request affects lenders' willingness to lend* is tested. As indicated in Table 13, the mean is 3.41 with standard deviation 1.03. The distribution of number of friends bidding shows most of respondents select 3 (neutral), followed by 4 (agree). To investigate the relationship between independent and dependent variables using logistic regression, the estimated coefficient (β value in Table 14) is positive (.463). With a p-value .001, this indicates a significant relationship. Hypothesis 4b is accepted. Additionally, in Table 14, the odds ratio, Exp(β), is 1.589. It means with some hypothetical modifications about the number of borrower's friends bids, lenders have an increased score by one category (e.g. from 3 to 4 on a likert scale). The logistic model can suggest that lenders' willingness to lend is 1.589 times affected.

Age of borrower

The eighth independent variable about young borrower is being tested. By analyzing the logistic regression, *hypothesis 5a age of borrowers affects lenders' willingness to lend* is tested. As indicated in Table 13, the mean is 3.20 with standard deviation 1.04. The distribution of young borrower shows most of respondents select 3 (neutral), followed by 4 (agree) and 2 (disagree). To investigate the relationship between independent and dependent variables using logistic regression, first, the estimated coefficient (β value in Table 14) is positive (.068). The result of statistical analysis did not reveal significant effect of age of borrower on willingness to lend (p= .626). Thus, hypothesis 5a is rejected, and further interpretation of odds ratio is not meaningful.

Appearance

The ninth independent variable about trustworthy appearance is being tested. By analyzing the logistic regression, *hypothesis 5b borrowers who appear trustworthy affect lenders' willingness to lend* is tested. As indicated in Table 13, the mean is 2.70 with standard deviation 1.21. The distribution of trustworthy appearance shows most of respondents are not influenced by appearance, and people who select 1 (strongly disagree) till 4 (agree) are distributed quite evenly. To investigate the relationship between independent and dependent variables using logistic regression, first, the estimated coefficient (β value in Table 14) is positive (.116). The result of statistical analysis did not reveal significant effect of appearance on willingness to lend (p= .341). Thus, hypothesis 5b is rejected, and further interpretation of odds ratio is not meaningful.

Geographic resemblance

The tenth independent variable about geographic resemblance is being tested. By analyzing the logistic regression, *hypothesis 5c geographic resemblance affects lenders' willingness to lend* is tested. The study result of Ravina (2007), which was based on the American context, indicates that when lenders find the borrowers coming from the same hometown or living in the same city, lenders will have more likelihood to lend. As indicated in Table 13, the mean is 2.76 with standard deviation 1.17. The distribution of geographic resemblance shows most of respondents select 3 (neutral), followed by 2 (disagree), 4 (agree) and 1 (strongly disagree). To investigate the relationship between independent and dependent variables using logistic regression, first, the estimated coefficient (β value in Table 14) is positive (.088). The result of statistical analysis did not reveal significant effect of age of borrower on willingness to lend (p= .483). Thus, hypothesis 5c is rejected, and further interpretation of odds ratio is not meaningful.

5.5.3 Relationships between attributes of loan request and willingness to lend

Loan amount

The eleventh independent variable of this study is about loan amount. As explained previously, Kumar (2007) indicated loan amount has positive association with default rate, while default rate is negatively related to willingness to lend. In order to test *hypothesis 6a loan amount affects lenders' willingness to lend*, the logistic regression are analyzed. As indicated in Table 13, the mean is 3.78 with standard deviation .83. The distribution of loan amount shows most of respondents select 4 (agree), followed by 3 (neutral) and 5 (strongly agree). To investigate the relationship between independent and dependent variables using logistic regression, the estimated coefficient (β value in Table 14) is positive (.481). With a p-value .007, this indicates a significant relationship. Thus, hypothesis 6a is accepted. Additionally, in Table 14, the odds ratio, Exp(β), is 1.617. It means with some hypothetical modifications about loan amount (i.e. increase the loan amount), lenders have an increased score by one category (e.g. from 3 to 4 on a likert scale). The logistic model can suggest that lenders' willingness to lend is 1.617 times affected.

Repayment period

The last second independent variable about repayment period is being tested. As mentioned before, repayment period has negative effect on default rate, thus the longer repayment period stimulates lenders' willingness to lend (Mild et al., 2015). In order to test *hypothesis 6b repayment period affects lenders' willingness to lend*, the logistic regression are analyzed. As indicated in Table 13, the mean is 3.85 with standard deviation .95. The distribution of repayment period shows most of respondents select 4 (agree), followed by 5 (strongly agree) and 3 (neutral). To investigate the relationship between independent and dependent variables using logistic regression, first, the estimated coefficient (β value in Table 14) is positive (.283). The result of statistical analysis did not reveal significant effect of repayment period on willingness to lend ($p = .064$). Thus, hypothesis 6b is rejected, and further interpretation of odds ratio is not meaningful.

Interest rate

The last independent variable about interest rate is tested. Wan et al. (2016) found that in China lenders' decision making is affected by the perceived benefits, thus higher interest rate seems more attractive for Chinese lenders. In order to test *hypothesis 7 interest rate affects lenders' willingness to lend*, the logistic regression are analyzed. As indicated in Table 14, the mean is 3.94 with standard deviation .94. The distribution of interest rate shows most of respondents select 4 (agree), followed by 5 (strongly agree) and 3 (neutral). To investigate the relationship between independent and dependent variables using logistic regression, first, the estimated coefficient (β value in Table 14) is positive (.031). The result of statistical analysis did not reveal significant effect of interest rate on willingness to lend ($p = .842$). Thus, hypothesis 7 is rejected, and further interpretation of odds ratio is not meaningful.

5.6 Robustness test

To test the robustness of this study, three groups of respondents were selected, which are the group of 211 respondents from WJX, the group of 145 respondents with P2P experience, and the group of 96 respondents without P2P experience. I ran the same logistic regression analysis with these groups. As summarized from Table 14, for the whole sample, the top 4 important factors are verified documents, safety protection (or service quality), low transaction fee and friends' endorsements from a borrower. Each of the groups yields similar result.

Table 18 indicates the logistic regression model for respondents from WJX (N=211), and it shows that top 3 important factors (verified documents, safety protection or service quality and low transaction fee) are the same as the whole sample. Yet, the factor of high loan amount is at the fourth place, which is slightly different from the whole sample. Table 19 indicates the logistic regression model for respondents with P2P experience (N=145), and its result is the same as the previous group. This is because 137 out of 145 respondents with P2P experience were collected via WJX, and that is why they yield the same result. Table 20 indicates the logistic regression model for respondents without P2P experience (N=96), and it shows the same result as the whole sample. As a result, three robustness checks yield similar result / rank, which means our research findings are very robust to different subsamples.

Logistic regression: variables in the equation				
	B	Wald	Sig.	Exp(B)
P1_LowTransactionfee	.665	14.144	.000**	1.944
P2_ServiceQuality	.929	20.517	.000**	2.532
P3_SafetyProtection	.949	23.827	.000**	2.584
B1_VerifiedDoc	1.323	25.274	.000**	3.755
B2_AccumTrans	.409	5.785	.016**	1.505
B3_FriendEndores	.434	8.013	.005**	1.544
B4_MoreFriendsbid	.495	9.767	.002**	1.640
B5_YoungBorrower	.060	.164	.686	1.062
B6_TrustAppearance	.150	1.310	.252	1.162
B7_GeoResemblance	.098	.542	.462	1.103
I1_HighLoanAmount	.509	7.416	.006**	1.633
I2_LongRepayPeriod	.283	3.441	.064	1.326
I3_HighInterestRate	.031	.040	.842	1.031
Constant	-4.678	10.737	.001**	.009

Table 18. Logistic regression result (respondents from WJX, N=211)

Note: The statistical significance of each β coefficient is tested by using Wald test. ** represents *significant in 95% confidence level.*

Logistic regression: variables in the equation				
	B	Wald	Sig.	Exp(B)
P1_LowTransactionfee	.692	9.128	.003**	1.998
P2_ServiceQuality	.952	12.544	.000**	2.592
P3_SafetyProtection	1.084	17.227	.000**	2.957
B1_VerifiedDoc	1.360	16.936	.000**	3.897
B2_AccumTrans	.592	7.208	.007**	1.808
B3_FriendEndores	.423	4.758	.029**	1.527
B4_MoreFriendsbid	.420	4.535	.033**	1.522
B5_YoungBorrower	.035	.037	.848	1.035
B6_TrustAppearance	.047	.085	.771	1.048
B7_GeoResemblance	-.054	.111	.739	.948
I1_HighLoanAmount	.860	9.859	.002**	2.363
I2_LongRepayPeriod	.417	3.781	.052	1.518
I3_HighInterestRate	.061	.082	.775	1.062
Constant	-5.286	6.725	.010**	.005

Table 19. Logistic regression result (respondents with P2P experience, N=145)

Note: The statistical significance of each β coefficient is tested by using Wald test. ** represents *significant in 95% confidence level.*

Logistic regression: variables in the equation (N=96)				
	B	Wald	Sig.	Exp(B)
P1_LowTransactionfee	.717	7.753	.005**	2.048
P2_ServiceQuality	.843	9.978	.002**	2.322
P3_SafetyProtection	.761	9.249	.002**	2.139
B1_VerifiedDoc	1.076	9.501	.002**	2.932
B2_AccumTrans	.395	2.823	.093	1.484
B3_FriendEndores	.521	5.165	.023**	1.684
B4_MoreFriendsbid	.472	4.557	.033**	1.603
B5_YoungBorrower	.109	.217	.641	1.115
B6_TrustAppearance	.164	.701	.402	1.179
B7_GeoResemblance	.294	1.809	.179	1.341
I1_HighLoanAmount	.167	.502	.479	1.182
I2_LongRepayPeriod	.145	.435	.510	1.155
I3_HighInterestRate	-.036	.024	.877	.965
Constant	-4.890	5.218	.022**	.008

Table 20. Logistic regression result (respondents without P2P experience, N=96)
Note: The statistical significance of each β coefficient is tested by using Wald test. ** represents *significant in 95% confidence level.*

5.7 Multicollinearity diagnosis

Multicollinearity is a common problem in linear regression, which happens in logistic regression as well. It happens when there is high correlation among independent variables, which may bring about unreliable regression coefficients and research findings. As indicated in correlation table (see appendix 7), there is a very strong positive correlation[20] between "service quality" and "safety protection" (r = .853, p = .000). Thus it is wise to check if our model involves multicollinearity issues.

The most widely-used for multicollinearity diagnosis is variance inflation factor (VIF). The larger the VIF is, the more likely there are multicollinearity issues in the model. There is no standard cut value for VIF. Generally, in logistic regression, when VIF is above 2.5, researchers may need further investigations (Olague et al., 2007). The results of multicollinearity diagnosis (see appendix 8) illustrate that "service quality" and "safety protection" may have multicollinearity issues with other 11 predictors, since the VIF values of both predictors vary from 3.9 to 4.9. As a result, "service quality" and "safety protection" may have similar effect to willingness to lend. The following table indicates when "service quality", for instance, is omitted, multicollinearity is not a problem, as VIF of "safety protection" reduced to 1.596.

[20] According to Evans (1996), the strength of correlation is segmented: 00-.19 "very weak"; .20-.39 "weak"; .40-.59 "moderate"; .60-.79 "strong"; .80-1.0 "very strong".

Coefficients [a]

	Collinearity Statistics	
	Tolerance	VIF
P3_SafetyProtection	.627	1.596
B1_VerifiedDoc	.393	2.541
B2_AccumTrans	.546	1.832
B3_FriendEndorse	.706	1.416
B4_Nr_of_Friendsbid	.657	1.523
B5_YoungBorrower	.763	1.311
B6_TrustAppearance	.569	1.758
B7_GeoResemblance	.560	1.787
I1_HighLoanAmount	.571	1.751
I2_LongRepayPeriod	.628	1.592
I3_HighInterestRate	.905	1.105

a. Dependent Variable: P1_ low_transactionfee

Table 21. Result of multicollinearity diagnosis when "service quality" is omitted

5.8 Summary of hypothesis test

Eight out of 13 hypotheses are statistically significant. Namely these variables (transaction fee, service quality, safety protection, verified documents, accumulated transaction and repayment history, friends' endorsement, the number of friends bid and loan amount) have impact on willingness to lend. On the other hand, five hypotheses (age, appearance of the borrowers, geographic resemblance, repayment period and interest rate) are rejected, since the result of statistical analysis did not reveal significant effect on willingness to lend.

Demographic information is quite controversial among scholars, because some of them argued that demographic information is considered as the important factor for lenders to make lending decisions (Bachmann et al., 2011; Chen & Han, 2012; Herzenstein et al., 2008); whereas Ashta and Assadi (2009), Berger and Gleisner (2007) and Kumar (2007) found that borrowers' demographic characteristics might influence on lending success. In this study, three demographic characteristics were tested, which are borrower's age, appearance and geographic resemblance. Based on the analysis of this study, it concludes that demographic characteristics have no or little impact on lenders' willingness to lend, since they are not statistically significant to have relationship with willingness to lend.

	Hypothesis	Results
Characteristics of platforms	Hypothesis 1. Transaction fee of a platform affects lenders' willingness to lend.	Accepted
	Hypothesis 2a. Service quality of a platform affects lenders' willingness to lend.	Accepted
	Hypothesis 2b. Safety protection of a platform affects lenders' willingness to lend.	Accepted

Characteristics of borrowers	Hypothesis 3a. Verified documents from a borrower affect lenders' willingness to lend.	Accepted
	Hypothesis 3b. The accumulated transaction and repayment history of a borrower affect lenders' willingness to lend.	Accepted
	Hypothesis 4a. The endorsement of a borrower's friend affects lenders' willingness to lend, when borrowers and endorsers are strangers to the lender.	Accepted
	Hypothesis 4b. The number of friends bidding for the same loan request affects lenders' willingness to lend.	Accepted
	Hypothesis 5a. Age of borrowers affects lenders' willingness to lend.	Rejected
	Hypothesis 5b. Borrowers who appear trustworthy affect lenders' willingness to lend.	Rejected
	Hypothesis 5c. Geographic resemblance affects lenders' willingness to lend.	Rejected
Characteristics of loan requests	Hypothesis 6a. Loan amount affects lenders' willingness to lend.	Accepted
	Hypothesis 6b. Repayment period affects lenders' willingness to lend.	Rejected
	Hypothesis 7. Interest rate affects lenders' willingness to lend.	Rejected

Table 22. Summary of hypothesis test results

6. Conclusions

In this chapter, major findings and practical implications are given along with the answers to research question. Then limitations and suggestions for future research are introduced.

6.1 Major findings and implications

This research aims to address the research question: *What are the determinants of lending decisions for Chinese peer-to-peer lenders?* Thus, to discover the most important determinants for Chinese lenders is an essential task. After reviewing prior literature, 13 hypotheses were proposed, and tested by an online questionnaire. Table 22 gives a complete overview that 8 hypotheses are consistent with the prediction, and 5 hypotheses are rejected, as the p-value is not significant in logistic regression.

Based on research result, five important predictors appear to have relatively strong impact on lenders' willingness to lend. Firstly, <u>verified document</u> is the most important predictor among others. Here we could deem that verified documents have positive impact on lenders' willingness, as lenders desire to have high-quality signals about borrowers. As prior research applied 4 verified documents (verified identity, marital status, income, and credit) to test it, they were used in this research as well. Out of 4 verified documents involved in this research, verified income, credit and identity have stronger correlation with willingness to lend than marital status. For platforms, it is very important to carefully check these documents. In order to quickly raise funds, it is also important for borrowers to hand in these documents to give lenders a high-quality signal, since they strongly impact lenders' willingness to lend. As a result, current or potential lenders can be aware whether a borrower has these documents verified.

Secondly, <u>safety protection</u> and <u>service quality</u> provided by platforms are second important predictors. Here we could deem that both predictors have positive impact on lenders' willingness, as lenders desire to have a safe system with high service quality. However, these are the factors that lenders cannot easily check. Thus, in order to make lenders satisfied, platforms should enhance and advertise their safe system and good service, since they are proved to be very important to lenders. Other than that, low transaction fee also impacts lenders' decision making. While enhancing safety and service, platforms may consider decrease transaction fee in order to attract more lenders.

Thirdly, predictors of social network are also essential – <u>endorsement from borrower's friend</u> and <u>number of friends</u> who join the loan request. This is because if there are lenders who are close friends with borrowers, they are more likely to select the right borrowers, and are able to force the borrowers to repay the loan. Endorsement from borrower's friend is an important signal especially for people who have no experience with P2P lending. Thus, borrowers may invite more of their friends to the loan request or ask for help promote in order to reach the targeted amount more quickly. On top of that, platforms could consider improving searching function to allow lenders sort loan requests based on friend's involvement. As a result, current and potential lenders could use friendship as a signal for decision making.

The above findings reveal Chinese lenders' willingness to lend is affected by the quality of platforms and borrowers, rather than perceived benefit. In conclusion, the factors of "verified documents", "safety protection from platforms (or service quality provided by platforms)", "endorsement from borrower's friend" and "number of borrower's friend bid" are the important determinants of lending decisions for Chinese P2P lenders.

6.2 Limitations and suggestions for future research

This research is subjected to three limitations. Firstly, when respondents answered questions with adjectives like high, low, trustworthy, etc., it may create bias for the research result, as people have different definitions with high, low, etc. Since to find articles that have specified the threshold is difficult in P2P lending field, future researchers may try to determine the variables more specific in order to improve research quality. Second is about the limitation of questionnaire design. The question in the main context "when I make a lending decision" was a two-way question, thus respondents may follow the thinking of "make a lend-out decision" or "make a not-to-lend decision" to answer how much each independent variable affects their decisions. Even though the Chinese expression is prone to the impression of "make a lend-out decision", it still may create a two-way direction for some people. Future researchers should avoid it by asking one direction in a clear way. Except that, Question 6 was for asking respondents' experience and willingness to lend about P2P. Although this question is logically correct with answers covered all possibilities, it is better to ask experience and willingness separately. The reason is that people with P2P experience may interfere their willingness to lend or lending behavior, and may bring about different results. To avoid it, future research should draw a "storyline" to make sure that respondent's willingness is influenced by the specific variables asked in the questionnaire rather than P2P experience. For example, questions could be "I would like to lend, if this borrower's income has been verified" or "I would like to lend, if many of this borrower's friends joined this bidding". Then at last, future researcher could ask "Are you willing to lend / invest to this borrower". By asking this way, researchers could get more relevant answers, since respondents' willingness is related to the factors that are asked in the questions. Lastly, except the 13 variables, there must be other important determinants of lenders' willingness. For instance, prior research found the purposes of wedding and repaying credit card are less risky, while small business and educational purposes are the riskiest for an American context (Serrano-Cinca et al., 2015). This could be the reason to influence lender's decision, thus future research may test which types / purposes of loan can stimulate lender's willingness for a different context.

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Appendices

Appendix 1. Different ways of assessment in the US and China

As mentioned before, communication between borrowers and lenders is only happened online. So lenders have to assess the creditworthiness of borrowers based on the information that is shown on the platform, and make decisions accordingly. The following explains different methods of credit assessment between two countries.

There are several methods that have been adopted by different P2P lending platforms to assess the creditworthiness of borrowers. One example is that Prosper.com in the US consults the third party, such as Fair Isaac Credit Organization (FICO), to assess the borrowers' credit score according to their social security number (Chen & Han, 2012). FICO score is one of the mostly used credit score assessments in the American P2P lending market. It scores from 300 to 850, which means the higher score a borrower reached the more creditworthy he / she seems to be. Similar to Standard & Poor's credit rating scale, it scales from AA (excellent) all the way to C or D, see below. According to the data analysis from Prosper, if a borrower has bad credit record in a traditional financial institute, he / she will hardly borrow loans via P2P lending platforms (Klafft, 2008).

Category:	HR	E	D	C	B	A	AA
Score:	520-559	560-599	600-639	640-679	680-719	720-759	760-900

Indication of Standard & Poor's credit rating scale

On the contrary, this third authentic party involved scenario does not apply in developing countries like China, since there is no such agency available in China (Chen & Han, 2012). The Chinese P2P lending credit scoring system is quite different and not as authentic as the developed countries. As mentioned in the lending process, there are two sorts of third party in China – online payment platforms and insurance companies. The credit score is computed from the record submitted by the borrowers (Chen & Han, 2012), which is lack of reliability. Yet, unlike traditional e-commerce for product or service exchange, the escrow system does not work the same for online P2P lending. Since the lenders' funds are the exchange item, to obtain more information about the borrower's creditworthiness becomes very essential to the lending outcomes (Chen et al., 2014). When some of the SMEs perform more creditworthy, My089 (Hongling Capital) will grant them with AA credit scoring certificate (see below), which is assessed by Hongling Capital risk management committee. Although some platforms in China provide the function that allows lenders to add non-creditworthy borrowers to their black list, it does not prevent the risk that the same borrowers register and use another account to create loan requests again.

Illustration of credit score certificate granted by Hongling Capital

Appendix 2. Three ways of interest rate setting

There are three ways that Chinese P2P lending platforms apply to set interest rate, and sometimes one platform may use different ways according to different loan products. Some platforms use so-called auction process[21] (Galloway, 2009), which means borrowers can set the maximum of interest rate they are willing to pay. Platforms like prosper.com (US) and ppdai.com (China) apply it. With auction process, lenders can bid the amount they want to lend and the minimum interest rate they will accept. Even when the loan is fully funded, lenders can still undercut the interest rate to edge out other lenders before the request closed. In the end, bids with lower interest rate are selected, and those lenders will be paid with the highest interest rate from the same request, although there are even lower interest rates. The second way is that some platforms are responsible to calculate the interest rate based on borrower's financial and demographic status. The third way is that platforms give a certain range and let the lenders set the interest rate within that range. The bidding process ends when the loan is fully funded, and further bidding will not result in any changes of interest rate (Collier & Hampshire, 2010). From these three ways of interest rate setting, it can be seen that interest rate is possible to be determined by all stakeholders (platforms, borrowers or lenders).

[21] Interest setting information is also summarized by Chinese websites, such as http://study.anxin.com/learn/knowledge/wangdai-405.html, http://www.wodai.com/n_licai/atrcle_72977.html, http://blog.sina.com.cn/s/blog_436fc5b60101qio6.html

Appendix 3. Comparison between the US and Chinese P2P lending market

P2P in China vs. in US

	China	US
Regulation	No	Well developed
Competition	Too many competitors	96% of the market is dominated by two players: Lending Club and Prosper
Borrowers	SMEs and individual	Individual
Credit system	Incomplete	Sophisticated
Risk control	Off-line dual diligence or guarantee	Credit rating
Risk tolerance	Weak	Strong
Business model	Capital pool	Information platform

Summarized by China Europe International Business School

Appendix 4. Online questionnaire (English)

Dear Participants,

Thank you for taking part of this survey about Chinese P2P lending. Via this survey we will better understand your lending experience. Based on the result, we will provide some suggestions for your future lending or other potential lenders. So your participation is priceless. This survey will take approximately 5 minutes. It is promised that your personal opinions and experience will be kept confidentially. Many thanks for your time and help!

Kind regards,
Fanlu Meng

Brief about online P2P lending: Peer to peer lending refers to the actions of direct lending and borrowing among private individuals occur without traditional financial institutions serving as intermediaries, while happen on the online basis. As an emerging form of lending, its significant development brought pressure for traditional lending industry. Compare to traditional lending, P2P lending is easy to handle, high interest, low transaction fees, and no need to mortgage, however, with higher risk. Nowadays, P2P lending platforms produced various loan products according to customers' demand, and more and more Chinese people choose this way to invest.

Question 1. Attributes of **lending platforms**

When I make a lending decision, the following aspects about lending platform matter.
(1= strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree)

	1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree
Platforms with low transaction fee	o	o	o	o	o
The platform guarantees borrowers' quality	o	o	o	o	o
The platform provides reliable service	o	o	o	o	o
The platform provides service and support during repayment period	o	o	o	o	o
The platform has sufficient security means to protect users	o	o	o	o	o
Transactional information is protected from being destroyed or altered during a transmission on the internet	o	o	o	o	o
I feel safe to make transaction	o	o	o	o	o

Question 2. Attributes of **borrowers**

When I make a lending decision, the following aspects about borrowers matter.
(1= strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree)

	1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree
Borrower's identity card has been verified	o	o	o	o	o
Borrower's marital status has been verified	o	o	o	o	o
Borrower's income has been	o	o	o	o	o

verified					
Borrower's <u>credit</u> has been verified	o	o	o	o	o
Accumulated transaction and repayment history of a borrower	o	o	o	o	o
Endorsement of a borrower's friend, while I don't know the borrower and endorser	o	o	o	o	o
Many of borrower's friends joined the same bidding	o	o	o	o	o
Borrowers are young (younger than 35 years old)	o	o	o	o	o
Borrowers who appear trustworthy	o	o	o	o	o
Borrowers come from the same city / province as me	o	o	o	o	o

<u>Question 3. Attributes of **information on loan requests**</u>

When I make a lending decision, the following aspects about the information on loan requests matter. (1= strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree)

	1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly agree
High loan amount	o	o	o	o	o
Long repayment period	o	o	o	o	o
High interest rate	o	o	o	o	o

4. Gender
   - o Male
   - o Female
5. Age
   - o Younger than 25 years old
   - o 26-35 years old
   - o 36-45 years old
   - o 46-60 years old
   - o Older than 60 years old

6. Have you had the experience with P2P lending?
   - o Yes, and I'm willing to invest via P2P in the future. (Go to Q7, and stop)
   - o Yes, but I'm not willing to invest via P2P again. (Go to Q7 and 8)
   - o Not yet, but I'm willing to try. (Stop)
   - o No, and I'm not planning to try. (Go to Q8)

7. Which of the following P2P lending platforms do you often use? Maximum three platforms can be selected.
   - ☐ PPDai（http://www.ppdai.com/）
   - ☐ Hongling capital（http://www.my089.com/）
   - ☐ Jinxin（http://www.jinxin99.cn/）
   - ☐ Weidai（https://www.weidai.com.cn/）
   - ☐ Tuandai（http://www.tuandai.com/）
   - ☐ GQGET（https://www.gqget.com/）
   - ☐ Yirendai（https://www.yirendai.com/）
   - ☐ IQIANJIN（http://www.iqianjin.com/）
   - ☐ Xinhehui（https://www.xinhehui.com/）
   - ☐ Other, name is _______

8. For what reasons, you don't want to invest / stop investing via P2P?
   - ☐ Default of platforms
   - ☐ Safety issues of platforms
   - ☐ Late repayment from borrowers
   - ☐ Illegal funding
   - ☐ Other _______

Appendix 5. Online questionnaire (Chinese)

调查问卷

大家好！

本人是一名在荷兰留学的研究生，很感谢大家参与这份关于中国网贷的问卷。我们想更好地了解您的贷款经验，从而为未来和潜在出借人提供一些意见，所以您的参与非常的宝贵。填写这份问卷大概需要 5 分钟。您的意见和资料将会慎重保存。非常感谢您的宝贵时间和参与！

网络贷款简介：在本调研中，网络借贷(P2P)是指个体和个体之间通过互联网平台实现的直接借贷。P2P 作为新型借贷平台，其快速增长的同时也给传统借贷带来了压力。与传统借贷相比，网络借贷操作简单、收益高、手续费用低、无须抵押，但也存在较高的风险。现如今，网贷平台根据客户需要推出了多种理财产品，越来越多的国人选择网络贷款进行

个人理财。

1. 关于**网贷平台**

当我做出借款决定的时候，我的借款意愿将会被下面的因素所影响。
（1=非常不同意，2=不同意，3=不确定，4=同意，5=非常同意）

	1 非常不同意	2 不同意	3 不确定	4 同意	5 非常同意
平台收取较少的交易手续费	o	o	o	o	o
平台可以保证借款人的品质	o	o	o	o	o
平台能提供可靠的服务	o	o	o	o	o
平台在还款期间对贷款人提供服务和支持	o	o	o	o	o
平台有充分的安全保障来保护用户	o	o	o	o	o
在网上交易时，交易信息能得到保护而不被毁坏或改变	o	o	o	o	o
交易时感觉安全	o	o	o	o	o

2. 关于**借款人**

当我做借款决定的时候，我的借款意愿将会被下面的因素所影响。
（1=非常不同意，2=不同意，3=不确定，4=同意，5=非常同意）

	1 非常不同意	2 不同意	3 不确定	4 同意	5 非常同意
借款人的身份证已被验证	o	o	o	o	o
借款人的婚姻状况已被验证	o	o	o	o	o
借款人的收入证明已被验证	o	o	o	o	o
借款人的信用证明已被验	o	o	o	o	o

证					
借款人累计转款和还款记录	o	o	o	o	o
借款人朋友的背书/推荐，我并不认识此借款人和他的朋友	o	o	o	o	o
借款人有多个朋友参与此贷款	o	o	o	o	o
年轻的借款人（小于 35 岁）	o	o	o	o	o
借款人长得靠谱	o	o	o	o	o
借款人和我同乡	o	o	o	o	o

3. 关于**借款信息**

当我做借款决定的时候，我的借款意愿将会被下面的因素所影响。
（1=非常不同意，2=不同意，3=不确定，4=同意，5=非常同意）

	1 非常不同意	2 不同意	3 不确定	4 同意	5 非常同意
借款数目高	o	o	o	o	o
偿还期长	o	o	o	o	o
收益高	o	o	o	o	o

4. 性别
   - o 男
   - o 女

5. 年龄
   - o 25 周岁以下
   - o 26-35 周岁
   - o 36-45 周岁
   - o 46-60 周岁
   - o 60 周岁以上

6. 您有没有过网贷投资经验？
    - o 有过，并有意愿继续通过 P2P 理财
    - o 有过，但不想通过 P2P 理财
    - o 还没有，不过有意愿尝试
    - o 还没有，也不打算尝试

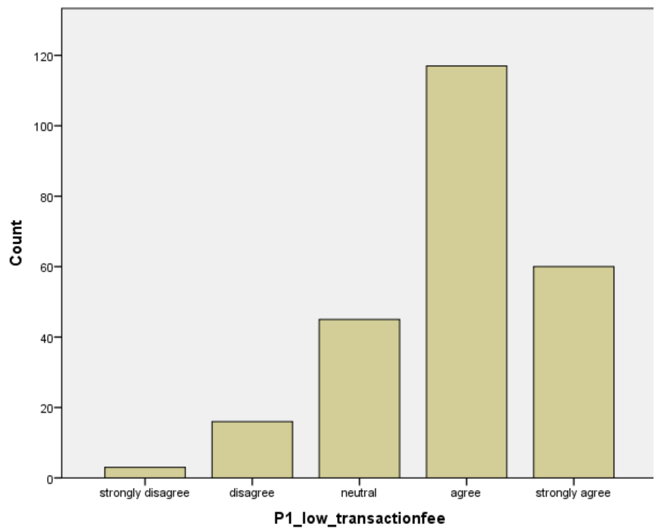
7. 您经常使用的借贷网站？最多选三个。

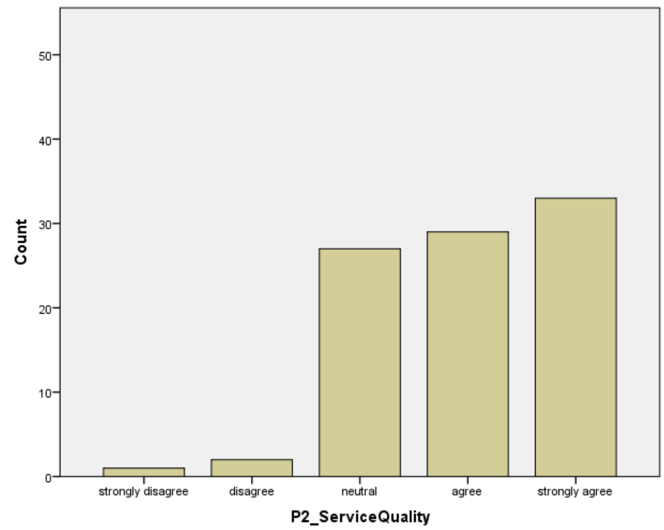
    - □ 拍拍贷
    - □ 红岭创投
    - □ 金信网
    - □ 微贷网
    - □ 团贷网
    - □ 冠 e 通
    - □ 宜人贷
    - □ 爱钱进
    - □ 鑫合汇
    - □ 其他 _______

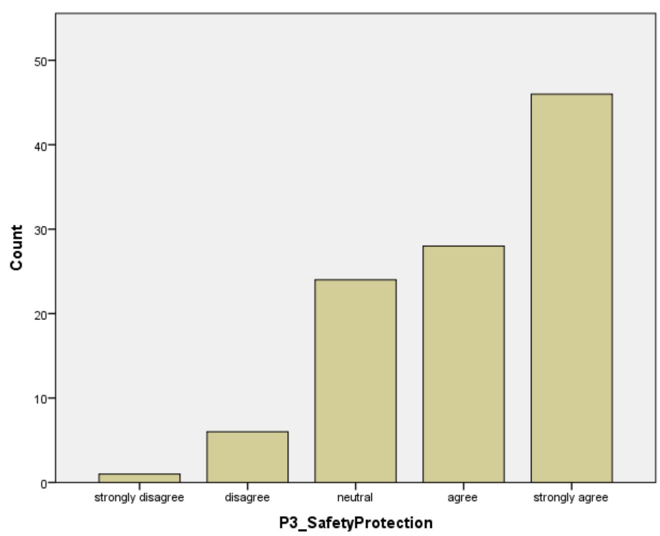
8. 以下哪些因素使您不愿（继续）通过 P2P 理财？

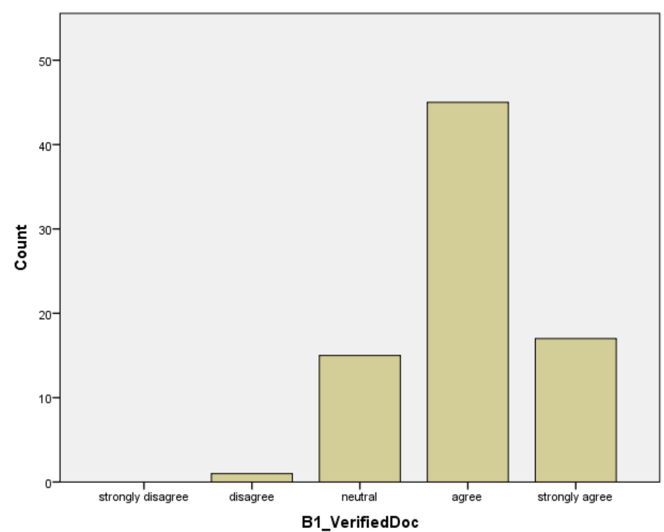
    - □ 平台跑路
    - □ 平台存在安全隐患
    - □ 逾期未还
    - □ 非法集资
    - □ 其他________

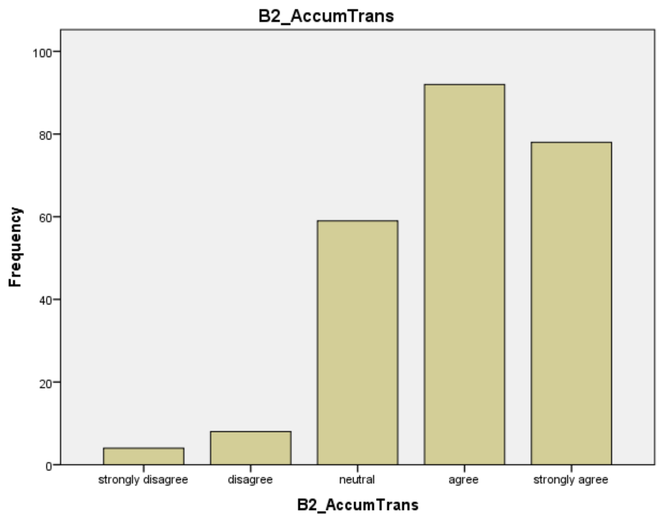
Appendix 6. Distribution of each independent variable in bar charts

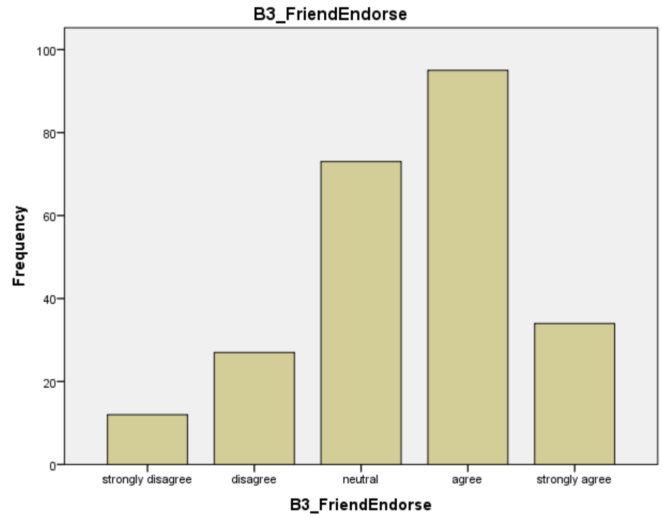


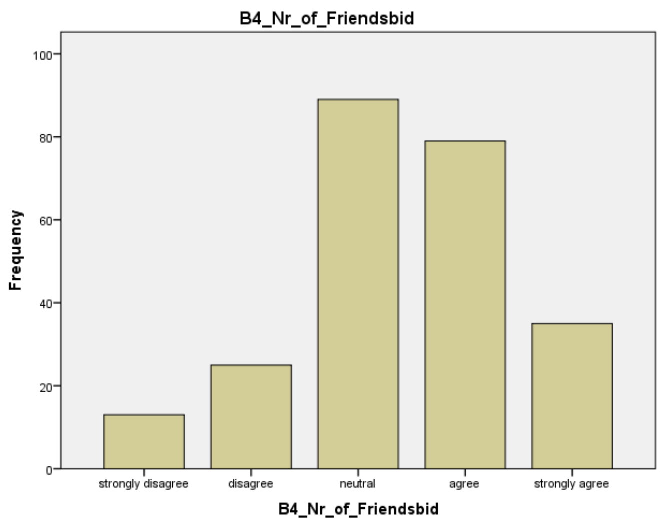


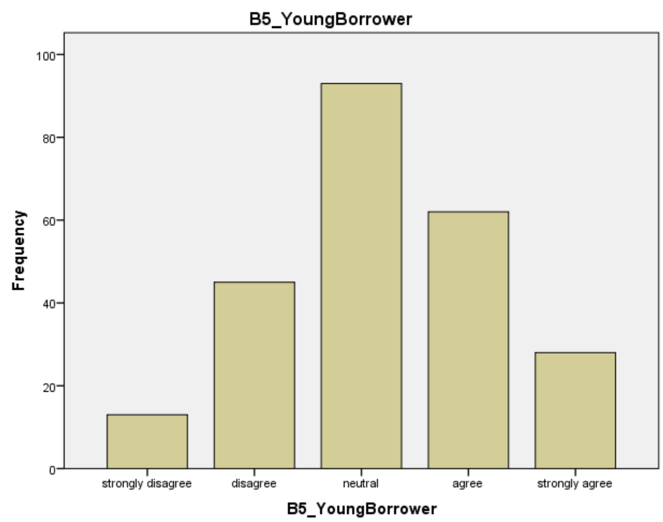


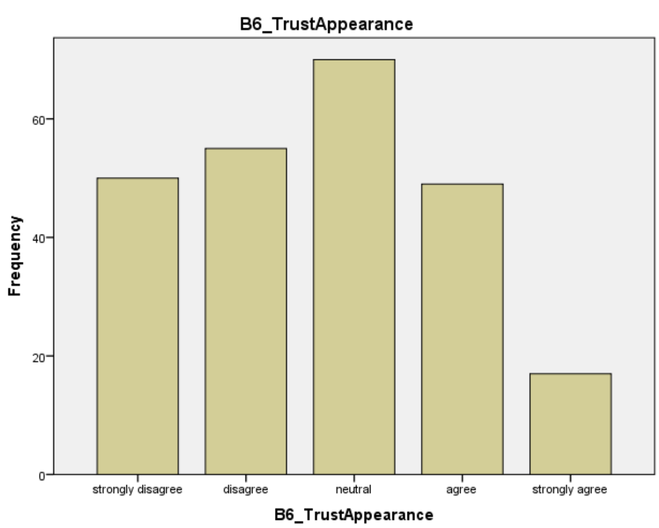


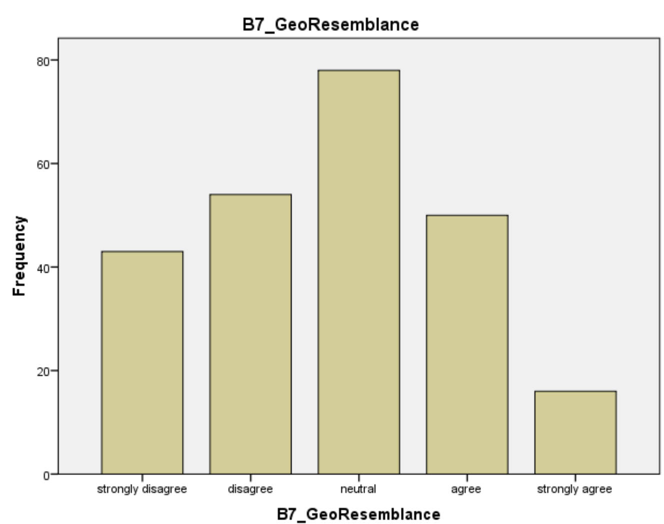

B2_AccumTrans
Frequency
0
20
40
60
80
100
strongly disagree
disagree
neutral
agree
strongly agree
B2_AccumTrans

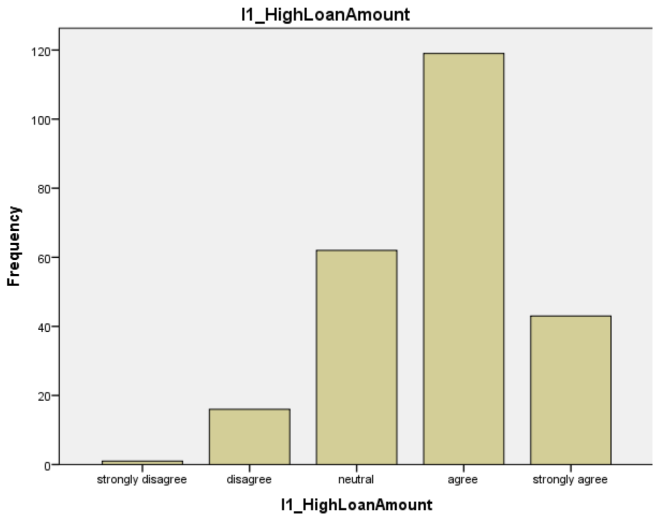

B3_FriendEndorse
Frequency
0
20
40
60
80
100
strongly disagree
disagree
neutral
agree
strongly agree
B3_FriendEndorse

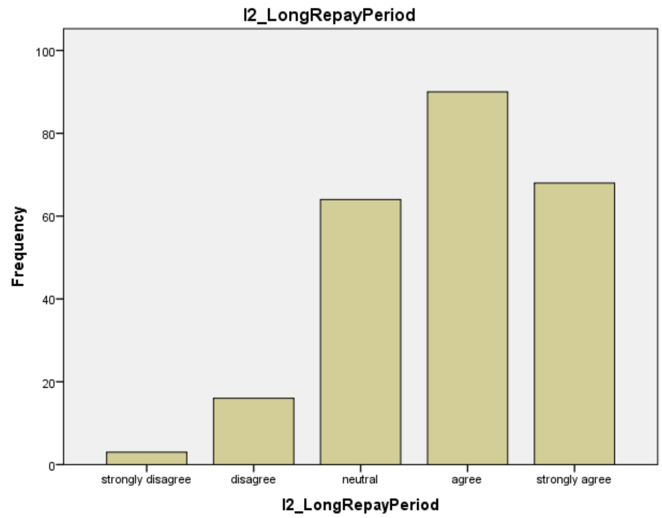

B4_Nr_of_Friendsbid
Frequency
0
20
40
60
80
100
strongly disagree
disagree
neutral
agree
strongly agree
B4_Nr_of_Friendsbid

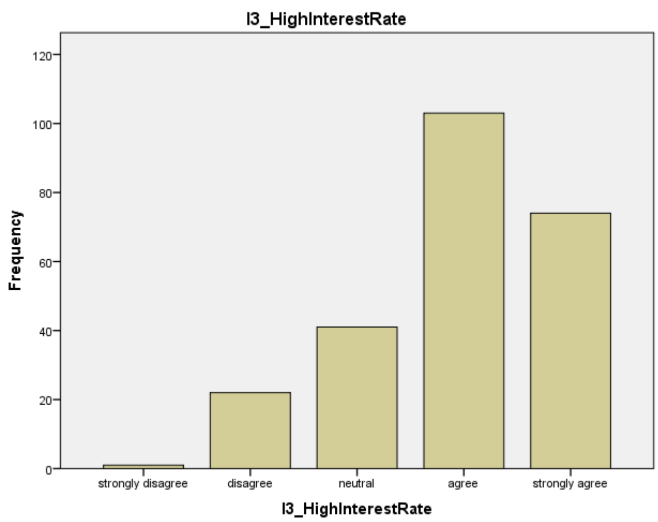

B5_YoungBorrower
Frequency
0
20
40
60
80
100
strongly disagree
disagree
neutral
agree
strongly agree
B5_YoungBorrower


B6_TrustAppearance
Frequency
0
20
40
60
strongly disagree
disagree
neutral
agree
strongly agree
B6_TrustAppearance


B7_GeoResemblance
Frequency
0
20
40
60
80
strongly disagree
disagree
neutral
agree
strongly agree
B7_GeoResemblance


I1_HighLoanAmount
Frequency
0
20
40
60
80
100
120
strongly disagree
disagree
neutral
agree
strongly agree
I1_HighLoanAmount


I2_LongRepayPeriod
Frequency
0
20
40
60
80
100
strongly disagree
disagree
neutral
agree
strongly agree
I2_LongRepayPeriod


I3_HighInterestRate
Frequency
0
20
40
60
80
100
120
strongly disagree
disagree
neutral
agree
strongly agree
I3_HighInterestRate

Appendix 7. Correlations among variables

		Q6a[22]	P1	P2	P3	B1	B2	B3	B4	B5	B6	B7	I1	I2	I3
Q6a	Pearson Correlation	1													
	Sig. (2-tailed)														
	N	241													
P1	Pearson Correlation	.284**	1												
	Sig. (2-tailed)	.000													
	N	241	241												
P2	Pearson Correlation	.330**	.610**	1											
	Sig. (2-tailed)	.000	.000												
	N	241	241	241											
P3	Pearson Correlation	.351**	.579**	.853**	1										
	Sig. (2-tailed)	.000	.000	.000											
	N	241	241	241	241										
B1	Pearson Correlation	.363**	.443**	.642**	.587**	1									
	Sig. (2-tailed)	.000	.000	.000	.000										
	N	241	241	241	241	241									
B2	Pearson Correlation	.200**	.347**	.489**	.408**	.661**	1								
	Sig. (2-tailed)	.002	.000	.000	.000	.000									
	N	241	241	241	241	241	241								
B3	Pearson Correlation	.226**	.199**	.254**	.267**	.315**	.207**	1							
	Sig. (2-tailed)	.000	.002	.000	.000	.000	.001								

[22] Q6a: willingness to lend; P1: LowTransactionfee; P2: ServiceQuality; P3: SafetyProtection; B1: VerifiedDoc; B2: AccumTrans; B3: FriendEndores; B4: MoreFriendsbid; B5: YoungBorrower; B6: TrustAppearance; B7: GeoResemblance; I1: HighLoanAmount; I2: LongRepayPeriod; I3: HighInterestRate.

	N	241	241	241	241	241	241	241							
B4	Pearson Correlation	.210**	.236**	.241**	.240**	.258**	.095	.464**	1						
	Sig. (2-tailed)	.001	.000	.000	.000	.000	.143	.000							
	N	241	241	241	241	241	241	241	241						
B5	Pearson Correlation	.031	.063	.079	.069	.090	-.027	.175**	.339**	1					
	Sig. (2-tailed)	.628	.333	.219	.289	.162	.677	.006	.000						
	N	241	241	241	241	241	241	241	241	241					
B6	Pearson Correlation	.061	.016	.066	.006	.010	-.029	.307**	.351**	.363**	1				
	Sig. (2-tailed)	.343	.802	.310	.929	.872	.657	.000	.000	.000					
	N	241	241	241	241	241	241	241	241	241	241				
B7	Pearson Correlation	.045	.003	.015	.028	.059	-.032	.257**	.355**	.412**	.617**	1			
	Sig. (2-tailed)	.485	.964	.820	.670	.362	.625	.000	.000	.000	.000				
	N	241	241	241	241	241	241	241	241	241	241	241			
I1	Pearson Correlation	.177**	.219**	.367**	.348**	.414**	.326**	.132*	.087	.099	.028	.047	1		
	Sig. (2-tailed)	.006	.001	.000	.000	.000	.000	.041	.178	.127	.660	.465			
	N	241	241	241	241	241	241	241	241	241	241	241	241		
I2	Pearson Correlation	.120	.156*	.335**	.266**	.357**	.273**	.082	.034	.047	-.004	-.007	.594**	1	
	Sig. (2-tailed)	.062	.015	.000	.000	.000	.000	.206	.598	.468	.953	.912	.000		
	N	241	241	241	241	241	241	241	241	241	241	241	241	241	
I3	Pearson Correlation	.013	.131*	.263**	.154*	.205**	.142*	.045	-.040	-.090	-.056	-.116	.224**	.121	1
	Sig. (2-tailed)	.842	.042	.000	.017	.001	.028	.483	.536	.162	.388	.073	.000	.061	
	N	241	241	241	241	241	241	241	241	241	241	241	241	241	241

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix 8. Results of multicollinearity diagnosis

Coefficientsa

Model		Collinearity Statistics	
		Tolerance	VIF
1	P2_ServiceQuality	.213	4.697
	P3_SafetyProtection	.250	4.000
	B1_VerifiedDoc	.382	2.621
	B2_AccumTrans	.535	1.870
	B3_FriendEndorse	.703	1.422
	B4_Nr_of_Friendsbid	.655	1.527
	B5_YoungBorrower	.762	1.312
	B6_TrustAppearance	.552	1.813
	B7_GeoResemblance	.553	1.809
	I1_HighLoanAmount	.569	1.759
	I2_LongRepayPeriod	.615	1.626
	I3_HighInterestRate	.857	1.167

a. Dependent Variable: P1_low_transactionfee

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	B3_FriendEndorse	.705	1.418
	B4_Nr_of_Friendsbid	.653	1.532
	B5_YoungBorrower	.767	1.303
	B6_TrustAppearance	.551	1.814
	B7_GeoResemblance	.553	1.808
	I1_HighLoanAmount	.572	1.749
	I2_LongRepayPeriod	.613	1.632
	I3_HighInterestRate	.860	1.163
	P1_low_transactionfee	.600	1.667
	P2_ServiceQuality	.205	4.880
	P3_SafetyProtection	.249	4.019
	B1_VerifiedDoc	.506	1.974

a. Dependent Variable: B2_AccumTrans

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	B7_GeoResemblance	.752	1.329
	I1_HighLoanAmount	.569	1.759
	I2_LongRepayPeriod	.613	1.632

	I3_HighInterestRate	.857	1.167
	P1_low_transactionfee	.599	1.670
	P2_ServiceQuality	.208	4.810
	P3_SafetyProtection	.252	3.966
	B1_VerifiedDoc	.387	2.585
	B2_AccumTrans	.533	1.876
	B3_FriendEndorse	.724	1.381
	B4_Nr_of_Friendsbid	.654	1.529
	B5_YoungBorrower	.773	1.294

a. Dependent Variable: B6_TrustAppearance

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	I2_LongRepayPeriod	.839	1.192
	I3_HighInterestRate	.883	1.133
	P1_low_transactionfee	.598	1.671
	P2_ServiceQuality	.202	4.939
	P3_SafetyProtection	.250	3.998
	B1_VerifiedDoc	.385	2.601
	B2_AccumTrans	.536	1.866
	B3_FriendEndorse	.703	1.422
	B4_Nr_of_Friendsbid	.648	1.544
	B5_YoungBorrower	.766	1.305
	B6_TrustAppearance	.551	1.814
	B7_GeoResemblance	.553	1.808

a. Dependent Variable: I1_HighLoanAmount