Essays on Peer-to-Peer Lending

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Abstract

This thesis includes three empirical papers focusing on individual’s behaviour in online lending markets.

The first chapter uses unique data from a leading P2P lending platform in China, *Renrendai.com*. We investigate how past loan portfolio performance affects individual investors' decisions to use the auto-investing tool. The estimates suggest that poorly performing investors are likely to switch to the auto-bidding tool after a spell of investment mistakes. At the same time, good performers prefer making decisions themselves in the self-directed mode. Additionally, experience of investors plays an essential role in adopting automation. The findings also provide evidence that the auto-bidding toolbox does not discriminate against borrowers with a specific gender, marital status, and financial literacy characteristics.

The second chapter studies the impact of a funding supply shock on loan concentration. Our analysis exploits a quasi-natural experiment involving the 2017 Chinese financial announcement, which imposed restrictions on overseas transfers and transactions. This regulation influenced the money and spending power of investors on *Renrendai.com* platform. Our data suggest that loans became less concentrated, inferring that investors are less likely to be attracted to listings. In particular, this disinterest is explained by the reduction in interest rates which led individuals to concentrate their attention on more profitable investments. Moreover, borrowers reduced the requested loan amounts and increased the repayment duration to gain investors' trust in repaying their money.

The third chapter investigates the impact of experience on decision making in peer-to-peer lending platforms. Our data span from October 2010 until October 2018 and is collected from *Renrendai.com*. The estimates suggest that experienced lenders are more likely to make suboptimal financial decisions. In particular, as investors become more experienced, they are more likely to become overconfident which makes them attempt more suboptimal financial decisions. Moreover, when investors are considered naïve or inexperienced, they are less likely to experience the impact of overconfidence on their financial outcomes. Lastly, not only are investors less efficient when bidding on loans, but they are also more likely to bid on less profitable loans compared to their portfolio performance.

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Chapter 1: Thesis Overview

1.1. Introduction

FinTech markets have overgrown in recent years and played a part in developing economies and financial markets. In many advanced and emerging market economies, consumers have openly adopted financial services like Fintech credit and relied on them as a primary source of income. Lending and borrowing are traditionally known as a process that goes through a bank-based financial system. Peer-to-peer (P2P) lending is the process of lending money to individuals, or organizations, using advanced online financials platforms (Tao et al., 2017). Since the launch of the first P2P lending platform in the United Kingdom, called Zopa in February 2005, these lending platforms made sure that these services can be done without the interference of a financial intermediary while providing lower prices than traditional financial markets (Bachmann et al., 2011). Zopa was considered as an opportunity to make a boom in the global financial lending markets. Based on that perspective, two online lending platforms were introduced to the United States of America: Prosper and Lending Club. As for the Chinese market, P2P lending started with Paipaidai.com as the first platform to offer such services in August 2007. This platform was then followed by another one, which is Renrendai.com with more than 23 million registered users and is considered as an A-Level credit ranked personal financial information service platform by the Chinese government. It has huge information on daily transactions that occurred on that platform and recorded more than 170,000 registered lenders and a total lending amount of over 10 billion dollars.

Peer-To-Peer lending has grown rapidly between 2011 and 2015 in China resulting in 3500 lending platforms and raising 980 billion yuan from total loans. Since then, the P2P lending markets have promptly been developing with more than 2,000 P2P lending platforms by the end of 2016. The P2P market's share has surpassed 91 billion dollars of the total outstanding loans in 2016. Individuals or companies with limited or no access to bank loans and investors who invested in these platforms are the reason behind the growth of this global online phenomenon. Despite the introduction of a new law that reduced the annual returns from 20% to almost 11%, investors did not stop funding loans and investing in the P2P platform.

Back in 2007, and with the rise of P2P phenomena, investors underwent solid losses and high risk because of the interest of lower quality borrowers in investing in the P2P markets. As a response to this concern in July 2015, the Chinese authorities released reforms and regulations that demand the registration of online P2P lending platforms as “information agency” firms with the authorities. They also required that these platforms channel incoming funds to a third-party depository bank account in order to declare the ownership of funds. A great number of P2P platforms have decided to either change their business types or to shut down due to intervention from the Chinese authorities. The wdzj.com website that collects aggregate data on the state of P2P lending in China has found that the number of platforms engaged in normal operations has dropped from 5,890 to 2,281 by the beginning of 2017.

According to the data provided by wdzj.com, a third-party website that provides a comprehensive data for Chinese P2P lending market, 1881 P2P platforms are operating up to the first half of 2018. The total accumulative transaction volume of P2P lending platforms has reached 7.33 trillion RMB. In the first half of 2018, the number of online borrowers and investors respectively reached 4.35 million and 4.08 million. However, in 2012, there are only 298 P2P platforms and loan volume is 22.9 billion RMB.

This thesis includes three empirical studies documenting the importance of some factors that affect individual's behaviour in P2P lending markets. These studies are essential for some main reasons. Firstly, investigating the changes in lenders’ investing strategy can help document the growing literature covering the adoption of automation in financial markets (see, e.g., D’Acunto et al., 2019). The technological developments that happened in the past decade have also developed online lending markets. P2P lending platforms are offering automated services to their clients in order to manage their portfolios. In particular, automation aims to make investors' lives easier by receiving the proper guidance from machines. In other words, in financial markets, automation achieves portfolio optimization for investors. Therefore, adopting automated financial services can help underperforming investors increase their portfolio performance (see, e.g., Rossi and Utkus, 2020).

Secondly, this study helps us explain individuals' reactions to a disruption event that changed the pattern of interest rates and money on the market. Particularly, the introduction of the 2017 financial regulation affected investor's spending power that happened in China. This change is reflected in the interest rates set by borrowers and in the concentration of the loans associated with investors. An increase in the funding available should increase the spending power of investors (see,e.g., Coën et al., 2018). However, the increase in spending power does not mean that investors are interested in investing in loans on Renrendai.com. This is because borrowers also reacted to financial regulation by lowering the interest rates and increasing repayment duration, making investing less interesting for bidders.

Thirdly, it helps us explain the existence of overconfidence, which can be vital when making decisions (see, e.g., Chuang and Lee, 2006; Malmendier et al., 2011). Notably, the change in the behaviour of experienced investors can be influenced by the existence of overconfidence and is reflected in investor’s financial outcomes. Experience, in general, should play a good role in shaping investor's performance. Therefore, an increase in investors' experience should increase their possibility of making suitable investments. However, this study is different since experience seems to have less influence on investors as we try to explain that it might be due to displaying a behavioural bias such as overconfidence. This behaviour can interfere with lenders’ judgment line, leading them to make suboptimal financial decisions.

The first chapter, “Peer-to-peer Investor Performance and Automatic Bidding,” documents how past portfolio performance affects lenders’ decisions to rely on an automated investing tool. This paper relates to three strands of literature in finance and economics. First, it contributes to the literature on adopting automated financial tools such as robo-advising by switching to an auto financing tool. Second, this study is related to the dynamic behaviour of investors over time. Our paper extends this literature by focusing on how the experience is vital for adopting the auto-toolbox. The third strand of literature focuses on discrimination in financial markets. Our study contributes to this literature by exploring the indiscriminate behaviour of the auto bidding tool.

The comprehensive dataset employed in the first chapter includes data at the investor-bid level from Renrendai.com. Importantly, this dataset has detailed information about the biddings placed on loans. In this chapter, we will be focusing on the importance of automation and portfolio performance. Renrendai.com offers their clients an automated bidding tool that can invest on behalf of them. Also, there are specific contracts that clients might sign that will allow them to use self-directed and automated methods. Therefore, since we investigate the switching behaviour between bidding methods, our exploration focuses on lenders who do hybrid investing. The whole sample includes more than 890,000 investors, with 824,686 investors deciding to use one bidding method, which is either an automatic method only or a manual method only. Thus, we ended up with 68,020 hybrid investors who decided to switch from one bidding method to another.

Our results provide evidence on the importance of the automated toolbox on *Renrendai.com*. More specifically, we first find a strong correlation between good portfolio performance and the auto-bidding tool. We also observe that investors with a lower portfolio performance are likely to switch to the automated mode after encountering several investment mistakes. However, users with good portfolio performance are more likely to rely on the self-directed mode. Moreover, our results show that as investors become experienced, they rely on the automated mode. In particular, the more individuals try the auto investing toolbox as they spend time on the market, the more they rely on the automatic bidding toolbox. Additionally, switching to automated services enhances investor's decision-making by attempting less sub-optimal financial decisions. Finally, fewer days spent between decisions result in a better financial outcome for investors.

The second chapter, titled “Funding Supply Shock and Loan Concentration” documents the response of individuals, both borrowers and investors, on *Renrendai.com* to a financial regulation affecting the money flow in China. This paper relates to the determinants of lending interest rates literature in P2P markets. We extend this literature by showing that financial regulation can also shape the returns that are offered on listings. Second, we contribute to the growing literature on customer concentration and performance. Our paper complements this strand of literature by showing that loan concentration is associated with higher returns for investors. Third, this paper is broadly related to the literature focusing on the transmission of disruption events via chains. This chapter is related to this literature by giving evidence on the impact of shock propagation through money chains on a crowdfunding platform.

We pursue our investigation using the same dataset used in the first chapter. However, the difference in this chapter is that we study it at the loan level. Also, we consider borrowers that have spent the whole time from 2010 to 2018 to study the regulation's impact. Our approach is to explore the response of Renrendai.com clients, borrowers and investors, to a financial regulation, which, in turn, affected the spending power of Chinese investors. Specifically, the 2017 Chinese regulation is used as a trigger of the money flow shock. This regulation started in July of 2017. The reason behind this is that capital outflows became a growing source of concern for the Chinese government in 2017 as it tries to get the economy back in the right direction and maintain currency stability without depleting the country's foreign exchange reserves. In particular, the currency fell to more than three trillion dollars in November 2016, hitting the lowest level at that time in nearly six years.

Our results show that the 2017 financial regulation substantially influenced the behaviour of individuals on *Renrendai.com*. Although this regulation sets restrictions on spending in China, the influence of this regulatory reform is still reflected of individuals on the market. First, we observe a fall in the concentration of loans from the investor's side, measured by several indicators like the Herfindahl-Hirschman Index. This drop in loan concentration can infer those lenders are less interested in investing in loans after the regulation. This disinterest shown by investors is due to the way borrowers reacted towards this event. Post-regulation, borrowers decreased the interest rates that are offered on loans. This can only mean that borrowers are taking advantage of lenders' increased spending power by making them gain lower returns since overseas transfers are now more challenging to attempt. At the same time, it is cheaper for borrowers to repay the fees when they lower the interest rates. Additionally, our results show that borrowers also increased the maturity of loans after the regulation. In other words, borrowers now have more time to repay the loan funds and do it with less monthly fees.

The third chapter, titled "Investor Expertise and Suboptimal Decisions" investigates the impact of several experience measures (e.g., bidding volume, active time, overall time, and successful investments) on decision making. Experience is cited as a positive factor for decision-making. However, in this chapter, we find that experience sometimes can be less efficient. In particular, we dug deeper into the argument and found out that experienced investors are likely to make sub-optimal financial decisions due to displaying overconfidence. This study contributes to several strands of literature. Firstly, this study contributes to the literature of learning from experience by contradicting the theory. Secondly, this study is related to the literature of determinants of financial decision-making by revealing the impact of overconfidence on investors' decision-making in microlending markets. Thirdly, we contribute to the literature on the influence of characteristics on decision-making. The most common finding is that better decision-making is associated with less discriminate investments.

The data employed in this chapter is the same as the one used in the previous chapters. The dataset contains more the 600,000 investors attempting more than 75 million bids between October 2010 and October 2018. This infers that more than seventy-five million decisions were attempted during that period. This data is unique and rich, allowing us to study the relation between experience and decision-making extensively. However, since overconfidence is a human behaviour, we decreased our sample size to approximately two million observations. This number of observations indicates the number of decisions that human individuals attempted during that time.

Our results show that an increase in the four measurements of experience is associated with worse decision-making. Higher bidding volume, successful bids, and more time spent on the market positively correlate with sub-optimal decisions. Moreover, we move on to drop the decisions that are fully attempted by machines on *Renrendai.com*. Instead, we keep users who only rely on self-directed bids. Our results show that experienced human investors are likely to make suboptimal financial decisions. However, naïve, or inexperienced individuals are less likely to make poor decisions. This result infers that when investors join the platform, they seem to be more cautious than when they become experienced. As they become experienced, overconfidence bias affected investors on Renrendai, leading them to make irrational decisions. Lastly, we find that specific borrower indicators, such as gender and financial literacy, explain investors' decision-making rationale. Thus, good decision-making prevails when investors attempt indiscriminate decisions that are linked to gender and financial literacy.

1.2. Renrendai.com platform

In the following three thesis chapters, we will use a unique dataset that is collected from a P2P lending platform called Renrendai.com. This platform was founded in 2010 (Liao et al., 2020) and is one of China's leading and fast-growing P2P lending platforms (Caglayan et al., 2020). Our dataset span from October 2010 to October 2018. In the three chapters, we will use the entire dataset from 2010 until 2018 but with differences that have to do with subsampling in each chapter which can lead to a reduction in the number of observations. In this section, we will present the process of Renrendai and how it operates.

The process for lenders is easier on Renrendai.com than for borrowers. For lenders, the process to register with the platform is more accessible than for borrowers. First, bidders or lenders need to register with the forum and have their verification process completed. After they get verified, they start to search for suitable loans and to fund them. Lenders can either fully fund or partially fund a loan where the later decision is considered less risky for investors. If it is partially funded, this infers that the listing was unsuccessful, and borrowers should incur no fees. On the other hand, investors will contribute to a loan and incur the time and transactional costs due to the failure to fund that loan. In addition to that, if investors fully funded a loan and the loan default, Renrendai.com guarantees that investors will be paid back in case that happened.[1]

[1] Renrendai.com reserve fund can cover possible defaults and late payments. This fund comes from the fees that the platform charges as service fees from customers. If the platform fails to collect back the loan, a collection agency will step in, and the money eventually collected will be put into the reserve fund.

As for borrowers, registering and getting verified is more challenging and can be done in two ways. The first way is based on an online authentication, and the other option is based on offline authentication. To start with the first option, to start looking for funds for their loans, borrowers need to submit their application form with their national identification number and provide additional personal details such as marital status, income, education, assets owned, certificates, and many more personal information. In addition, borrowers would also need to specify the loan amount, the interest rate they would offer, the purpose of the loan, and the duration for repaying the entire fund.[2] After submitting all this personal information, the platform will evaluate the borrower's application and assign a credit rating that varies between high-risk (HR) and very safe (AA). After borrowers have been assigned a credit rating, Renrendai charges these borrowers an initial service fee.[3] Within this context, investors will start to either wholly or partly fund the loan. If the target set has not been met, the loan will automatically fail and be labeled as a failure. Finally, after this lengthy procedure, borrowers still need to pay Renrendai.com some fees for service, certification, and management, which is considered another obstacle that borrowers usually face.[4]

The second option is done by applying to a Ucredit's branch requesting offline verification services.[5] After that, these documents will be checked and verified online. Finally, verified applications are transferred to Renrendai.com platform. After that, the process will be the same as the first option. The difference in using Ucredit is that borrowers will have an A-class credit rating. Those who attempt a non-offline verification process will have different class ratings.

This process that Renrendai adopts is very similar to other Chinese P2P lending platforms. First, the platform does not offer Web 2.0 functionality (Liu et al., 2018), implying that investors can only see basic loan information and cannot communicate with potential

[2] Interest rates can vary 6% to 24%. Maximum loan maturity is up to 3 years, and the loan amount that can be requested by borrowers vary between 3000RMB and 500,000RMB.

[3] AA, A, B, C, D, E, and HR, credit ratings should be charged an initial service fee that is equivalent to 0%, 1%, 2%, 2.5% 3%, 4%, and 5% respectively.

[4] Renrendai charges monthly management fees for loans that varies between very safe and high risk that can reach 0.88% per month. These fees are charged as follows. Monthly management fees of 0.55%, 0.60%, 0.65%, 0.70%, 0.75%, 0.80%, and 0.88% for loans that have AA, A, B, C, D, E, HR credit ratings, respectively

[5] Ucredit was founded in May 2011 in Shanghai and focuses on micro financing to individuals. In order to apply for micro loans using Ucredit, customers can follow one of the following four steps. First, a customer can submit an online application through their platform. Second, individuals can apply physically in one of the branches in China. Third, one can register using WeChat application which is equivalent to WhatsApp in China. Finally, an application can be made through Ucredits' customer service hotline. Ucredit focus on providing customers with two services. The first one is instant micro loans that targets individuals who have a credit line of up to RMB300,000 for the purpose of personal consumption. The second is elite micro loans that target civil servants, policemen, doctors, lawyers, and employees in large state-owned enterprises and banks.

borrowers. Second, although Renrendai has similarities with Chinese platforms, it has many differences from US platforms. [6]The main difference is that it is a pure modern online lending process. Also, it provides offline authentication to its customers in order to further reduce information asymmetry. Finally, they use in-house credit ratings to categorize borrowers according to risk.

1.3. Literature review

This section will present the literature that is related to our empirical studies. Each strand of literature will be linked and presented with each chapter. The three chapters contribute to several strands of literature in finance and economics.

1.3.1. Chapter 1

The first empirical chapter contributes to three strands of literature. The first contribution in this chapter relates to the literature on automated financial tools adoption. There is a growing literature that focuses on the adoption of a robo-advising tool. For example, D'Acunto, Prabhala, et al. (2019) studied a robo-advising tool in Indian markets from 2015 to 2017 that targets equities. Their results show that robo-advising is beneficial for those investors that are considered as ex-ante undiversified. In particular, they show that the automated tool can increase diversification hence reducing portfolio volatility. However, investors who have diversified portfolios fail to benefit from this automated robo-advising tool. Similarly, Reher and Sun (2019) found consistent results regarding diversification to those in D'Acunto, Prabhala, et al. (2019) while studying a US-based robo-advisor for long-term investing. However, the data for this study is only a one-year data that span from January to December 2015. They found out that investors with under diversified portfolios increase the likelihood of adopting robo-advising. Rossi and Utkus (2020) study a hybrid robo-advising tool and its impact on the portfolios of previously self-directed investors in U.S. markets using proprietary data from Vanguard and other data sources. Their data span from January 2015 to December 2017. Their study suggests that robo-advising reduces money market mutual funds holdings and increases bond holdings. Additionally, they found out that the automated tool eliminates home bias by significantly increasing international diversification. Also, their study suggests that robo-advising increases the risk-adjusted-performance.

[6] The main thing is that it is different from American P2P lending platform. For instance, users of Prosper.com can communicate with the potential borrowers which lead to exchanging information. Renrendai user cannot do that.

Robo advising does not only enhance diversification; it can also allow investors to control their spending behaviour. For example, D'Acunto, Rossi, et al. (2019) find that automated tools significantly impact user's consumption behaviour. They show that overspending users who invest through a FinTech app that provides salient peer information are likely to reduce their spending after signing up for the app. Lee (2019) studies individual's attitudes towards overspending alerts that are created using robo-advising algorithms. The author finds out that investors are likely to reduce their overspending behaviour after receiving warning alerts. Additionally, the author also finds that the alerts affect varies among different groups of people that are older, more financially savvy, and more educated in which investors react more towards these alerts. In a more recent study covering overspending, Gargano and Rossi (2020) based their study on two FinTech apps that are Gimme5 Italian platform and Acorn American platform. By using difference-in-differences approach, they show that when investors set goals for themselves, they are more likely to increase their savings rate by 90%. This result is robust to any goal that individual investors set. For instance, individuals who save for concrete objectives such as a car can achieve their goals as those who set goals with different aims other than concrete objectives.

Automated financial services can also help in consumer lending decisions. P2P lending platforms started recently to introduce automated lending decisions for their clients. For example, in a recent and related study conducted by D'Acunto, Ghosh, et al. (2021) studied an automated financial tool in order to investigate between lenders that rely on themselves and those who rely on machines. Their results show that investors who self-direct their investments tend to make investment mistakes, such as lending borrowers who share the same religion with lenders and lend to those with higher social class than others. This kind of decision end investors up with bad financial outcomes. When investors adopted the automated bidding tool, such behaviour biases started to be corrected by facing lower default rates (by 32%) and achieving higher returns (by 11%). Our analysis complements this literature by showing the importance of switching to an auto financing tool to help users with decision-making.

The second contribution in this study relates to the dynamic behaviour of investors over time. Barber and Odean (2001) show that rational investors trade only if the expected gains exceed transaction costs. Other experienced investors, such as overconfident ones, overestimate the precision of their information. Thus, they end up taking more financial risks. Bauer et al. (2009) studied the impact of trading on individual investor performance in the Netherlands from a prominent online discount broker. Their results suggest that experience affects investor's behaviour by increasing the likelihood of trading derivatives. Additionally, Grinblatt and Keloharju (2009) study the impact of sensation seeking and overconfidence on trading activity. Their results show that higher experience is associated with higher sensation seeking related to taking higher financial risks. Similar to the previous study, Hoffmann et al. (2015) use monthly survey data with matching brokerage records in order to examine investor perceptions and behaviour. Their study estimates show that as individuals become more experienced, they are likely to take more risks. Rossi and Utkus (2020) extend this to a robo-advsiing approach and found out that investors with lower self-directed trading experience are the ones who end up benefiting from the automated service. Our paper extends this literature by focusing on how the experience changes investor's perceptions by adopting the auto-toolbox.

The last contribution in this chapter is related to discriminatory practices by human investors in financial markets. Existing works, like Pope and Sydnor (2011) studied discrimination in a P2P lending platform called Prosper.com. They found evidence of racial disparities showing that investors are less likely to fund borrowers with a picture that displays their black skin colour. Moreover, Herzenstein et al. (2011) show how borrower identity claims can influence investor's funding decisions. For example, investors on the Prosper platform showed that they are more likely to fund a loan if the borrower number of identity claims increase. However, they found out that loan performance usually suffers.

Additionally, Duarte et al. (2012) proved that appearance triggers financial decisions. They showed that borrowers who appear trustworthy in their photographs are more likely to get their loans funded. Also, trustworthy borrowers are less likely to default, making the investor attempt a rational financial decision. Iyer et al. (2016) showed the effectiveness of market screening on the decisions made by investors. For example, they showed that investors on Prosper.com platform were 45% more accurate in predicting the likelihood of a borrower defaulting than using the borrower's exact credit score. The point behind stating this strand of literature is to show that human investors are prone to biases and discrimination. Other existing literature has shown that automated tools are likely to remove biases. For example, D'Acunto, Ghosh, et al. (2021) show that investors prefer to lend to individuals who share the same religion and avoid lending individuals from different religions. However, adopting an auto investing tool corrects such biases by letting investors lend to individuals from different backgrounds and religions. This chapter contributes to this strand of literature by exploring the indiscriminate behaviour of the auto bidding tool.

1.3.2. Chapter 2

This empirical chapter contributes to three strands of literature. First, it relates the determinants of lending interest rates literature in P2P markets. Most of the studies focus on Propser.com platform, where lenders control the interest rates and not the borrowers. These studies have found that certain factors can significantly determine the interest rate offered on loans. For example, Larrimore et al. (2011) show how statements associated with loans can define the rate of return (interest rate) on loans. In particular, if the loan description increased by 60 words over the average number of words, it would increase funding success, equivalent to reducing the borrower's maximum acceptable interest rate. Moreover, Michels (2012) studies the impact of unverifiable disclosures. The authors suggest that such disclosures negatively correlate with interest rates inferring a decrease in interest rates. Lin et al. (2013) investigate the impact of social capital and found that friendships lower the interest rates on funded loans. Additionally, Kgoroeadira et al. (2019) find that self-employed borrower, have lower credit ratings, and are renters with low income are less likely to get their loan funded and pay a high-interest rate. Our paper is different since the borrowers are the primary determinant in setting the interest rate. Ding et al. (2019) use data from Renrendai.com platform and examine the impact of historical performance. The findings of their study indicate that an enhancement in the economy can increase the interest rates charged. However, inflation significantly decreases the interest rates offered. Additionally, and coming to borrower characteristics, the estimates in their study show that borrowers with higher financial literacy and higher risk charge lower interest. We extend this literature by showing how financial regulations can also shape the returns offered on listings.

Second, this paper is related to the growing literature on customer concentration and performance. Pataoukas (2012) investigated the impact of customer concentration on supplier firm fundamentals and stock market valuation using data collected from Compustat, EDGAR, FASB, and SEC. The results of the study show a positive correlation between customer concentration and profitability. Irvine et al. (2016) extend previous studies and found that the concentration rate negatively relates to performance at the beginning of the relationship between customers and firms. However, as trust is built between the two parties, the correlation between customer concentration and performance becomes positive. In a more recent study, Grullon et al. (2019) investigated the relation between concentration indicators and profitability margins using a merged dataset from CRSP and Compustat throughout 1972-2014. The results of their study suggest that profit margins and mergers and acquisitions (M&A) deals are more profitable for a specific type of firm. These firms are in industries that have the most notable increases in product market concentration. Their results are robust to the inclusion of private firms, factors accounting for foreign competition, and the use of alternative measures of concentration. Their results also show that the increased profit margins associated with increased concentration translate into higher shareholder returns. These papers are studied at firm-industry levels. Our paper relates to this strand of literature by showing that the performance of the loan can decide the loans' concentration level at loan level in online lending markets.

Third, this paper is broadly related to the literature that focuses on the actual effects of money through its transmission channels. For example, Ranaldo et al. (2021) recently investigated the impacts of prudential regulation on short-term interest rates. They used data from November 2013 to December 2017 using unique regulatory data of CCP investment activity and repurchase agreements transactions and found evidence for the supply and demand channels. In particular, the regulation has had the effect of lowering short-term rates and increasing market imbalances in various ways, which has resulted in unintended consequences. Moreover, Forbes and Warnock (2021) study the relationship between sudden disruption events, like the global financial crisis and Covid 19, and extreme capital flow movements. Their study suggests that since these events, the movements of extreme capital flows have not increased. However, the drivers of these episodes appear to have changed since the global financial crisis. Also, they have shown how these disruption events can affect the long-term interest rates.[7] We add to this literature by focusing on how the money shocks transmit into crowd funding markets.

1.3.3. Chapter 3

The third empirical chapter also relates to three strands of literature in finance and economics. First, this study is related to the literature of behavioural determinants of investor’s decision-making. Previous works have often shed light on several factors that can interfere in an individual's decision-making. For example, starting with overconfidence, previous works (e.g., Barber and Odean, 2000, 2001; Odean, 1998, 1999) argue that a behaviour like overconfidence lets individuals overtrade, leading them to bear losses they did not expect. In support for this, Glaser and Weber (2007) use survey data and match it with investors' trading historical records. The authors document that the scores of overconfident investors are positively related to their

[7] See also other papers (e.g., Borio and Zhu, 2012; Bruno and Shin, 2015; Paligorova and Santos, 2017) have investigated risk-taking channel when covering loans in traditional markets. Additionally, See Cerutti and Hong (2021) analyse the evolution of disaggregate gross capital inflows from 2003 until 2016.

trading activity. Deaves et al. (2010) use also survey data, from a source called ZEW Finanzmarkttest, and this survey is conducted on a monthly basis. In particular, this data represents the records of financial market practitioners in Germany. The author's results suggest that market forecasters are overconfident because of miscalibration. At the same time, market experience does not lead forecasters to have better calibration. In a more recent study, Merkle (2017) used a panel survey of online brokerage clients in the UK and found out that financial overconfidence leads to increased trading activity, higher risk-taking, and less diversified portfolios.[8] Second, overreaction has been proven that they also shape investor's decisions. Lobe and Rieks (2011) studied the German market between 1988 and 2017 and found that investors can earn abnormal returns by exploiting the overreaction anomaly. Farag (2014) uses a sample size of daily data of companies that experienced a considerable one-day price change from the Egyptian stock market (EGX). The author found evidence of overreaction in the EGX. However, this overreaction was considered a short-term one. In particular, the coefficients for the initial abnormal returns (AR) on the day of the event are negatively significant for winners and losers. This infers that the smaller the negative shock, the larger the size of cumulative AR following the event. Additionally, herding behaviour has also been discussed before that it affects investor's decision-making. Zhang and Liu (2012) use a unique dataset from a leading P2P lending platform called Prosper.com, one of the largest platforms in the U.S. They found out that when investors rationally herd, they are likely to predict the creditworthiness of borrowers s by observing other's decisions and use borrower characteristics to moderate their inferences. In a more recent investigation, Jiang and Verardo (2018) found a negative relation between herding behaviour and skill in the mutual fund industry. In particular, they find that herding funds underperform their anti-herding peers by over 2% per year. They infer that the differences in skill drive among individuals drive the performance gap where the anti-herding individuals make superior financial decisions and can expect the trades of the crowd; furthermore, the herding-anti-herding performance gap is more comprehensive when skill is more valuable and more significant among managers with more substantial career concerns. Finally, Gao et al. (2020) expands the idea of herding and talks about expert imitation in P2P lending platforms. The authors pursue their study using data from Renrendai.com. They define experts as investors who either have higher centrality scores or put more effort into the network by spending more money and time. The author's results suggest that average investors mimic the bids of experts. Inactive lenders learn from the leading

[8] See also Grinblatt and Keloharju (2009); Deaves et al. (2009); Graham et al. (2009) for further evidence.

individual’s behaviour through observing their actions. However, they show that experts rarely imitate others that are considered experts. At the same time, experts exhibit herding behaviour. Our paper this strand of literature by showing that overconfidence interferes in investor's line of judgment.

Second, this chapter relates to the literature of learning from experience. Previous works have shown that as investors learn from their trading experience, they will likely engage in more speculative trading. Mahani and Bernhardt (2007) introduce a learning from trading model in order to explain several theories. The authors find that inexperienced investors are likely to bear huge losses inferring that they are not skilled enough. Moreover, the naïve individuals, or small speculators, quit trading and leave the market while those who survive and are considered experienced realize high profits. Also, the authors relate aggressive trading to psychological biases. Moreover, Seru et al. (2010) used a large sample of individual investors and found consistent results with Mahani and Bernhardt (2007). Their results drive two conclusions: investors become better with their trading experience, while other individuals leave the market after realizing losses and have poor skills. The second type explains a substantial part of overall learning by trading. Linnainmaa (2011) uses household data from Finland and estimates a structural model of learning from trading. The estimates suggest that individuals invest in order to learn from their mistakes. Even though investors do not believe in their trading abilities, they still are interested in trading. The findings also show that realized returns are considered a downward-biased measured of investor's skills and abilities. Our paper contradicts this literature by showing that experienced investors do not learn from their historical performance.

Lastly, this paper relates to the literature on over-investing. Several theoretical models have investigated the relation between active investing and overconfidence. Previous studies have shown that investor’s performance decreases due to showcasing overconfidence behaviour (Caballé and Sákovics, 2003; Daniel et al., 1998; Gervais and Odean, 2001; Kyle and Wang, 1997; Odean, 1998). Additionally, existing empirical studies have backed this argument. For example, Barber et al. (2009) studied the Taiwanese market and focused on the Taiwan Stock Exchange (TSX). The data that the author used span from 1991 to 1995. The authors investigated all stock trades attempted by investors during that period and found that active investing decreases the return of individuals' portfolios by 3.8 percentage points on a yearly basis. This percentage is equivalent to approximately 2% of the country’s GDP. Also, other studies like Glaser and Weber (2007) and Biais et al. (2005) found consistent results with Barbet et al. (2009) and linked this deterioration in portfolio performance with overconfidence behavior. Finally, Deaves et al. (2009) added to the literature by experimentally providing a piece of evidence between calibration-based overconfidence and trading where overconfidence allows investors to overtrade. Our paper complements this strand by showing that more bidding increases overconfidence, leading to increased suboptimal decisions.

Chapter 2. Peer-to-peer Investor Performance and Automatic Bidding.[9]

[9] In this chapter, we use material that is submitted to University of Birmingham for the assignment of Advanced Research Methods module and for the Annual Review.

2.1. Introduction

Recent advances in financial markets led investors to start thinking about new investing methods (see, e.g., An and Rau, 2021; Chiu and Koeppl, 2019; Goldstein et al., 2019). Robo-advisors appear to be an alternative method to a traditional human advisor and have emerged strongly in recent years (Alsabah et al., 2021). Investors have been relying on automated services due to the transparency and the systematic advice that it would give while mitigating biases that a human advisor would consider (Foerster et al., 2017). Moreover, investors rely on machines in active equity investments where machine learning algorithms identify outperforming equities.[10] This paper investigates how past loan portfolio performance affects the decisions of individual investors to use the auto-investing tool.

Automation was destined for success by overtaking the tasks that individuals would typically do (Barclay et al., 2006; Chen et al., 2019) or even making better decisions than humans (Agrawal et al., 2019; Brynjolfsson et al., 2019; Kleinberg et al., 2018). There are examples of using automation tools in the financial sector with regards to high-frequency trading (e.g., Hasbrouck and Saar, 2013; Menkveld, 2013), robo-advising (e.g., D'Acunto, Prabhala, et al., 2019; D'Acunto, Ghosh, et al., 2021; Rossi and Utkus, 2020), blockchains (e.g., Biais et al., 2019) or even in treasury securities (e.g., Fleming et al., 2018). Our empirical analysis extends these works by investigating automation in microlending markets.

To pursue our investigation, we use detailed data of biddings on listings from a leading Peer-to-Peer (P2P) lending platform in China, Renrendai.com, to study how portfolio performance can change investors' perceptions towards investing. The data span from 2010 to 2018 and have several unique aspects compared to traditional financial markets. First, peer-to-peer lending markets have lower transaction costs. As a result, the margin charged by a platform is much less compared to traditional banks. Second, there are low information costs: investors have access to a wide range of lending opportunities, each of them provides detailed information about borrowers. Finally, entry and exit costs into peer-to-peer lending markets are low, which could attract borrowers and lenders.[11] These features make the peer-to-peer market a well-suited environment for comparing manual and automatic investment decisions.

[10] See "Will bots replace humans in active equity investment?" (Financial Times, October 02, 2019) (Available at: https://on.ft.com/2Ovjmg9) , accessed on May 15, 2020.
[11] See e.g., Reher and Sokolinski (2020) where the platform that they study has a minimum entry requirement of 500$. See also https://renrendai.com/uplan.html for further information about Renrendai.com entry requirements.

Our results provide evidence on the importance of automation on *Renrendai.com*. First, our results suggest that better portfolio performance is associated with the usage of automation as an increase in portfolio performance increases the usage of automated biddings by 38 percentage points. Additionally, we observe the importance of switching to the automated tool. In particular, investors with low-performing portfolios are likely to switch to automated biddings by 7.1 percentage points. However, good performers tend to rely on themselves in the manual mode by 6.1 percentage points. Moreover, our results show that as investors become experienced, they are more likely to rely on the automated mode. In particular, the more individuals try the auto investing toolbox, the more they rely on the automated service. Also, relying on the auto-bidding enhance investors decision-making abilities. Finally, fewer days spent between decisions result in a better financial outcome for investors.

This paper relates to several strands of literature. First, this study contributes to the literature of adopting automated financial tools such as robo-advising. In particular, these studies discussed the importance of automation on portfolio performance and portfolio diversification (e.g., D'Acunto, Prabhala, et al., 2019; Rossi and Utkus, 2020), overspending behaviour (e.g., D'Acunto, Rossi, et al., 2019; Lee, 2019), durable investing (e.g., D'Acunto, Hoang, et al., 2021; D'Acunto and Rossi, 2021; Gargano and Rossi, 2020) and wealth investment (e.g., Rossi and Utkus, 2021).[12] Our analysis complements this literature by focusing on a decision to switch to an auto financing tool.[13] Second, this study is related to the dynamic behaviour of investors over time. A number of works (e.g., Barber and Odean, 2001; Bauer et al., 2009; Grinblatt and Keloharju, 2009; Hoffmann et al., 2015) have shown that as investors become experienced, they are likely to change their investing behaviour.[14] Our paper extends this literature by focusing on how the experience changes investors' perceptions by adopting the auto-toolbox. The third strand of literature focuses on discriminatory practices by investors in financial markets. Existing papers often focus on the discrimination attempted by human individuals (e.g., Campbell, 2006; Duarte et al., 2012; Herzenstein et al., 2011; Iyer et al., 2016; Lusardi and Tufano, 2015; Pope and Sydnor, 2011). Recent studies have shown how automated financial tools are likely to remove human discrimination (e.g., D'Acunto, Ghosh, et al.,

[12] See also Dietvorst et al. (2018) who presented automated services as an algorithmic model being adopted by participants and discussed the possibility of reducing algorithmic aversion

[13] The automated bidding tool in this paper allow investors also to use self-directed bidding mode. A robo-advising service tool let robo-advisors to take over and the human investor will have no control over their account. The only way the human can interfere in the decisions of a robo advisor is by cancelling the contract.

[14] These studies have shown how experience affect investors decision by taking excessive risk.

2021).[15] Our study contributes to this literature by exploring the indiscriminate behaviour of the auto bidding tool.

The rest of the study is structured as follows: Section 2.2 introduces our data and sample collection, section 2.3 reviews the methodology and introduces the econometric model used, section 2.4 presents our main results, and section 2.5 provides the conclusion of this paper.

2.2. Renrendai.com and auto bidding toolbox

Renrendai.com is a leading P2P lending platform (Caglayan et al., 2020) and was founded in 2010 (Liao et al., 2020). It has a AAA rating, which is the highest rating that the Chinese Academy of Social Sciences (CASS) can give for P2P lending platforms. By 2015, the platform recorded more than 2 million registered users and was considered in China's top 100 internet companies. Also, late in 2018, Renrendai.com had more than 1 million approved loans and achieved over 10 billion RMB total investment. With all these advantages, yet to get verified on this platform is still demanding for specific users.

On the one hand, for borrowers to apply for a credit loan that can vary from 3,000 RMB to 50,000 RMB, they must provide a lot of information such as marital status, monthly income, education level, gender, and other personal details. After submitting all these documents, the platform evaluates the borrower's application and gives the customers a credit rating that are as follows: AA, A, B, C, D, E, and HR (i.e., High Risk). These ratings allow investors to know the riskiness level of borrowers. On the other hand, it is much easier to get verified by the platform for investors. Bidders just need to register with the platform and have their verification process completed. After they register, they start to search for suitable loans and in order to fund them.

Using this platform, investors have the chance to choose an investment mode to follow. This strategy can either rely entirely on self-directed biddings, ultimately rely on automated biddings, or use a hybrid method which is a mix between self-directed and automated modes. For example, if investors decide to use the manual mode, they bid on loans using information that satisfy their preferences, such as bidding on a loan with the desired characteristics. Alternatively, if the automated services are used, there are no options for analysing information at the time of bids. Instead, a goal is set, and bidding is carried out using loan parameters.

[15] In their paper, they show how investors started to lend individuals that come from different background and religions after adopting an automated financial tool. Before that, investors used to trust and lend borrowers that come from the same religion as theirs.

Relying on machines has become very popular in the past decade.[16] The automatic toolbox we examine on this platform helps lenders carry out decentralized bidding and recurring lending according to the lender's bidding scope with no access to borrower characteristics. The only thing that an investor can look at is the bid amount to be invested, maturity, and the interest rate. After completing the authorized lending, the service automatically runs and invests in loans based on the services' algorithms.

The automated bidding tool is top-rated on *Renrendai.com* because it can save time for individuals as they do not have to analyse all the information displayed in front of them. For example, when clients observe what loans are listed on the market, the platform presents to them several unique aspects like the number of lenders and the number of times the automated bidding service was used to bid on this loan.[17] The automated tool on *Renredai.com* consists of three services. The first service is called the preferred service, and it can let investors have 12 months of continuous automatic bidding for a specific fee paid by investors. The second service consists of several fixed-term contracts, such as signing up for 3, 6, 9, or 12 months. After the duration is finished, the contract will expire and will be cancelled automatically. The final service consists of a fixed amount of investing in every month in the 1st year. All these services will not change the outcome when choosing one. It depends on the preferences of each investor. The differences between the three services are the duration of the service and the bidding amount by investors. Also, the platform promotes for the automated bidding service for investors cleverly. Renrendai.com automatically transfers the client to the automated options when an investor logs in to the platform and starts lending.[18]

2.3. Data description

We collect the data from Renrendai.com, and it spans from October 2010 to October 2018. 892,716 investors on this platform placed more than 75 million bids on approximately 0.6 million listings. First, we collect information on loans and borrowers for every unique submitted and approved application. Second, we gather investor-level data that is based on each bid's timestamp, the amount invested in each loan, and the bidding method to fund each loan. Combining these datasets, we obtain a sample of around 75 million observations at

[16] See Online Appendix of Figure FA2.1 that shows very popular platforms, like etoro in the UK and Robinhood in the US, provide automated services for their clients. All these companies are proposing a different frameworks and models, like robo-advising, robo retirement, to help individuals make better financial decisions.
[17] For example, see www.renrendai.com/uplan-37206.html for a sample loan where the platform shows that investors bid on this loan using the automatic bidding service by 252 times.
[18] See https://renrendai.com/premium.html for more information about the three services.

investor-bid level. Each loan application has financial information such as maturity, interest rate, the riskiness of the loan, as well as borrower characteristics such as monthly income, marital status, educational level, and gender of the borrower. Our exploration focuses on investors who do both manual and automated biddings. The entire sample includes 892,716 investors, with 824,686 deciding to use one bidding method, either an automatic or mode method. We end up with 68,020 investors who decided to switch from one bidding method to the other.

Table 2.1: Descriptive statistics, whole sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Obs.	Mean	Std	P25	P50	P75
Auto Bidding	74,529,079	0.96	0.20	1.00	1.00	1.00
Switch to Auto	74,529,079	0.01	0.08	0.00	0.00	0.00
Switch to Manual	74,529,079	0.01	0.08	0.00	0.00	0.00
Portfolio Performance	73,629,386	0.16	0.02	0.15	0.15	0.15
Profile Age	74,529,079	122.95	157.87	12.00	61.00	176.00
Successful Investments	74,519,308	376.94	702.51	35.00	132.00	415.00
Maturity	74,529,079	33.73	7.05	36.00	36.00	36.00
Credit Risky	74,529,079	0.01	0.08	0.00	0.00	0.00
Interest Rate (%)	74,529,079	10.28	0.96	9.60	10.20	10.20
Monthly Income	73,455,950	18902	14666	7500	15000	35000
Married	74,529,079	0.64	0.48	0.00	1.00	1.00
High Education	74,529,079	0.02	0.15	0.00	0.00	0.00
Gender	74,529,079	0.63	0.48	0.00	1.00	1.00
Days Since Last Decision	74,529,079	3.45	15.58	0.00	0.00	2.00
Decision Performance	72,691,175	-0.00	0.05	-0.01	0.00	1.00
Decision Profitability	73,535,694	-0.35	0.71	-0.25	0.00	1.00
Decision Riskiness	73,526,483	-0.72	8.03	0.00	0.00	0.00

Notes: This table shows the Number of Observations (1), Mean (2), Standard Deviation (3), and quartiles (4)-(6) of the following variables. Auto Bidding is a dummy variable that equals 1 if the investor uses automatic bidding, 0 = manual biddings. Switch to Auto is a binary variable that indicates that 1 = automatic switch, 0 = otherwise. Switch to Manual is a binary variable where 1 = manual switch, 0 = otherwise. Portfolio Performance is weighted by investor’s bid amounts and is a measurement for portfolio performance for each investor. Profile Age is investor’s profile age and is the active time (in days) spent in the market. Maturity is the maturity of the loan in months. Successful Investments are the cumulative number of successful and unique loans that individuals invested in. Credit Risky (1 = Yes) is a dummy where 1 = HR or E loan risk, 0 = otherwise. Interest Rate (%) is the interest earned on a loan. Monthly Income is borrowers' monthly income. Marital Status (1 = Married) is a dummy for borrowers where 1 = Married, 0 = otherwise. High Education (1 = Yes) is a dummy for borrowers where 1 = Masters or Above, 0 = otherwise. Gender (1 = Yes) is a dummy for borrowers where 1 = Male, 0 = Female. Days Since Last Decision is the days spent since the last decision made. Decision Performance is a measurement for decision making and is the difference between loan performance at time t and investor’s previous portfolio performance. Decision Profitability is a measurement for decision making and is the difference between loan return at time t and investor’s previous profitability. Decision Riskiness is a measurement for risk taking and is the difference between loan risk at time t and investor’s previous risk performance.

Table 2.1 provides basic summary statistics for the whole sample size. The table presents that 96% of bids are attempted using auto bidding toolbox, indicating this service's popularity on *Renrendai.com* platform. When it comes to switching, 1% of the time, investors recorded a switching to automatic action for investors. The same percentage applies to manual switching, where *Switch to Manual* has a mean of 1%. But this is for the overall sample size. Investor's portfolio performance is approximately 0.16 percentage of interest per 1 unit of risk on average with a deviation of 0.2. This implies that there is heterogeneity among investors where some perform better than others. For *Profile Age*, individuals spent approximately 123 active days on average on the platform. The number of *Successful Investments* is approximately 377. Additionally, on average, investors tend to bid on loans with a maturity of approximately 34 months, which are considered long-term investments.

Furthermore, on average, 1% of the loan's investors invested in were considered risky because a machine attempts most bids on renrendai.com. This will be further explained in Table 2.2 as well. Also, investors on average place bids on loans averaging 10% as interest with a standard deviation of 0.96%. Moreover, individual investors are associated with married, highly educated, and male borrowers by 64%, 2%, and 63%, respectively. The number of days spent between one decision and the other is 3.45 days.

Also, in this paper, we are interested in seeing the performance of investors using other measurements than portfolio performance. We introduce three measurements that can compare the previous performance of investors compared with what do they invest in. For example, *Decision Performance,* measures the difference between loan performance (based on reward-to-risk ratio) and investors' previous portfolio performance. The descriptive statistics show a weak negative mean of -0.00 which infers that investors on average are likely to make suboptimal financial decisions. As for *Decision Profitability*, it is the difference between loan return and investors' previous performance (previous profitability record). Table 2.2 shows that lenders are less likely to make decisions with better profitability than their current record by -0.35. Finally, for *Decision Riskiness,* it is measured by the difference between loan risk and investors' previous risk performance and this table shows that investors, on average, have a mean of -0.72 for this variable meaning that they are more aware when considering the risk of investments.

Table 2.2: Descriptive statistics: manual users vs automatic users

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean	Std	Mean	Std	Mean	Std	Diff
	Only Hybrid Users		**Only Manual Users**		**Only Automatic Users**		**Difference: Man vs Auto**
Portfolio Performance	0.16	0.03	0.15	0.15	0.16	0.01	-0.01***
Profile Age	206.86	203.48	37.10	67.01	84.33	111.77	-47.23***
Successful Investments	670.72	999.80	115.76	279.93	241.32	447.03	-125.56***
Maturity	33.21	7.56	20.84	12.18	34.11	6.58	-13.27***

Credit Risky	0.01	0.12	0.22	0.41	0.000	0.002	0.22***
Interest Rate (%)	10.63	1.21	12.47	2.53	10.09	0.68	2.38***
Monthly Income	17982	14749	18957	16789	19339	14583	-381***
Married	0.68	0.47	0.72	0.45	0.62	0.48	0.10***
High Education	0.02	0.15	0.02	0.15	0.02	0.15	0.000***
Gender	0.65	0.48	0.76	0.43	0.62	0.48	0.14***
Days Since Last Decision	2.80	18.88	10.58	45.22	3.69	13.04	6.89***
Decision Performance	-0.00	0.07	0.01	0.34	-0.00	0.01	0.02***
Decision Profitability	-0.63	0.89	0.20	2.85	-0.23	0.49	0.42***
Decision Riskiness	-2.39	12.69	5.36	42.58	0.02	0.87	5.34***

This table represents the t-test for the mean difference between variables for manual users and automatic users. Portfolio Performance is weighted by investor's bid amounts and is a measurement for portfolio performance for each investor. Profile Age is investor's profile age and is the active time (in days) spent in the market. Maturity is the maturity of the loan in months. Successful Investments is the cumulative number of successful and unique loans that individuals invested in. Credit Risky (1 = Yes) is a dummy where 1 = HR or E loan risk, 0 = otherwise. Interest Rate (%) is the interest earned on a loan. Monthly Income is borrowers' monthly income. Marital Status (1 = Married) is a dummy for borrowers where 1 = Married, 0 = otherwise. High Education (1 = Yes) is a dummy for borrowers where 1 = Masters or Above, 0 = otherwise. Gender (1 = Yes) is a dummy for borrowers where 1 = Male, 0 = Female. Days Since Last Decision is the days spent since the last decision made. Decision Performance is a measurement for decision making and is the difference between loan performance at time t and investor's previous portfolio performance. Decision Profitability is a measurement for decision making and is the difference between loan return at time t and investor's previous profitability. Decision Riskiness is a measurement for risk taking and is the difference between loan risk at time t and investor's previous risk performance.

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Table 2.2 presents the summary statistics for hybrid, manual, and automatic users. Also, it shows the t-test mean difference between manual and automated users. We observe that investors who rely on the automated mode have a better portfolio performance than those who rely on self-directed bids. The active days spent on the market by the automated users are longer than the manual users. Also, users who rely on automation are likely to make more successful investments than manual ones. Automation is also associated with long-term investments as shown by *Maturity*. Machines are known for investing in long-term projects as they are considered passive and more safe.

Additionally, the auto investing tool on renrendai.com places bids on risk-free loans, with a mean of 0% on credit risky loans. As a result of that, automatic users invest in loans that are less profitable than manual users. Therefore, this results in higher portfolio performance for automatic users over manual ones. Also, automatic users have a higher probability of investing with unmarried and females' borrowers. The days spent taking the next decision are less for automatic users, inferring that the automated mode is faster in decision-making. This is mainly because the decision will take less time to be analysed and processed by algorithms. We can see also that manual users make slightly better overall decisions and more profitable ones. However, automated users have less risky decisions by a significant margin.

When it comes to hybrid users, individuals perform just as good as automatic users. They have better portfolio performance and invest in long-term investments. Additionally, hybrid users have approximately 1% of their bids attempted on risky loans, implying that hybrid users rely on risky investments but do not often bid on them. Also, hybrid users are likely to invest in loans with a 10.63% return on average, which is higher than an automatic user. Finally, for *Days Since Last Decision*, hybrid individuals seem to take the least time in order to make their next move. They are likely to take less time to make their next decision.

2.4. Methodology

This section will present the methodology of this chapter. We present the way we measure the bid amount weighted average portfolio performance for individual lenders. Also, we introduce the econometric model.

2.4.1. Portfolio performance measurement

We construct a measure for portfolio performance by using investors' a reward-to-risk measurement that changes at the time of each bid depending on the historical performance. This measurement is inspired by what Calvet et al. (2007) and Von Gaudecker (2015) did in order to calculate the basic Sharpe Ratio.[19] Following this, we modified the portfolio performance measurement based on our data where the return is the interest rate, and risk is the credit score.

Interest rate is the interest earned on loans and has a range from 3% to 24.4%. Credit score is a numerical variable that ranges between 0 and 245 on the platform where 0 is the riskiest and 245 is the safest investment. However, the credit score needs adjusting since Renrendai displays it in a way where the higher the score, the better (safer). The more the score deviates from 0 the safer the investment is. We want to fix this issue in order to have a proper reward to risk measurement. For this reason, we modify the credit score by making it the higher the score, the riskier the investment. Mainly, we created a maximum credit score that holds a value of 246.[20] Then we subtract the maximum credit score from each loan credit score that is found on the platform in order to create a plausible risk measurement. Now, the risk measurement is constructed in a way where the more it deviates from 1, the riskier the investment. To make it clearer, the loan risk measurement is calculated as follows:

$$\text{Risk}_j = \text{Max Credit Score- Credit Score}_j \tag{2.1}$$

[19] In their papers, the Sharpe ratio equalled to annual excess return over standard deviation. In our paper, return and risk are at the time of the bid and not at an annual rate.
[20] The highest score is 245 as mentioned previously so this score is only greater by one unit.

Where subscript *j* is the loan. The risk measurement now is modified by using the difference between the maximum credit score on the platform and the credit score for each investment. Accordingly, the risk measurement is set in a way that the higher the credit score, the riskier the investment.

Now, as both return and risk are set it is time to add weights to these measurements. We weighted both return and the risk with investor's bid amounts to have a plausible measurement for portfolio performance. So, we compute the average portfolio performance across bids within a lender weighted by the bid amount. To simplify what has been done, let $\mathrm{Return}_{k,t}$ and $\mathrm{Risk}_{k,t}$ be, for example, the average return (interest) and risk (risk score) of lender *k* at time *t*, respectively. Where $\overline{\mathrm{Return}^{w}}$ and $\overline{\mathrm{Risk}^{w}}$ are the weighted average return and risk within a lender. *i* is a successful bid of lender *k* until time *t*. Therefore, the three-aggregate measures (denoted by $\overline{\mathrm{Return}^{w}}, \overline{\mathrm{Risk}^{w}}, \overline{\mathrm{Performance}^{w}}$) are computed as follows:

$$\overline{\mathrm{Return}_{k,t}}^{w} = \sum_{t} \mathrm{Return}_{k,i} * \frac{\text{Bid Amount}_{k,i}}{\sum \text{Bid Amount}_{k,i}}$$

$$\overline{\mathrm{Risk}_{k,t}}^{w} = \sum_{t} \mathrm{Risk}_{k,i} * \frac{\text{Bid Amount}_{k,i}}{\sum \text{Bid Amount}_{k,i}} \tag{2.2}$$

$$\overline{\mathrm{Performance}^{w}} = \overline{\mathrm{Return}_{k,t}}^{w} \Big/ \overline{\mathrm{Risk}_{k,t}}^{w}$$

2.4.2. Econometric specification

Investors who discriminate against a specific group of borrowers end up with worse-performing portfolios. Additionally, automated financial tools, such as robo-advising, in P2P lending markets can eliminate biases that bidders take and help select better-performing borrowers (e.g., D'Acunto, Ghosh, et al., 2021). What are the main characteristics that the Renrendai.com auto-bidding tool is correlated with in order to make these funding decisions? So, before addressing our main question about portfolio performance and changing investing mode, we would like to inspect the correlations between automatic biddings and characteristics of investors and loans. Our data is a panel data at investor-bid level. The investor is represented by a unique investor ID and the bid attempt is represented by the actual time of the bid (e.g., 13oct2010 08:51:10). In a linear probability model, we run the following specification at investor-bid level: [21]

$$\text{Auto Bidding}_{i,t} = \beta_0 + \beta_1 \text{Portfolio Performance}_{i,t-1} + \beta_2 \text{Loan}_{i,\gamma} + \beta_4 \text{Borrower}_{i,\gamma} + \delta_i + D_i + \varepsilon_{i,t} \quad (2.3)$$

Where subscript *i* indicates the investor and subscript *t* indicates the bid attempt for investor *i*. $AutoBidding_{i,t}$ is a dummy variable where 1 = bid attempted by automated services, 0 = manual bid attempt. $Portfolio\,Performance_{i,t-1}$ is the weighted average portfolio performance for investor *i* at bid attempt *t*. Portfolio performance measurement is described in detail in section 2.4.1. For the remaining explanatory variables, $Loan_i$ is a vector of loan characteristics that include the logarithm of one plus maturity of the loan, interest rate (%), and a binary variable that indicates the riskiness level of the loan (E or HR = Risky). $Borrower_{i,\gamma}$ is a vector of borrower characteristics that include the logarithm of one plus borrowers' monthly income, and dummy variables for marital status (1 = married), educational level (1 = High education), and gender (1 = Male). We expect to see a negative significance on variables that are associated with borrowers. The main reason behind this is that bids that are considered self-directed are attempted by humans, and according to several studies, investors are biased against certain groups of borrowers (e.g., see. Duan et al., 2020; Caglayan et al., 2020). So, the auto bidding tool should be less associated with males, married, higher income, and highly educated groups. δ_i is investor fixed effect and D_i is hour of bid fixed effect. The standard errors are robust and clustered at the individual investor and loan level. The description of all the variables is found in the Online Appendix of Table TA2.14

In what follows, model (1) cannot capture the changing behaviour of investors. One might argue that adopting the automated tool can enhance investors' performance on the market. For example, investors with low portfolio performance prefer to sign-up for an automated financial tool (e.g., Rossi and Utkus, 2020). So, we want to analyse past portfolio performance impact on investors' decision of changing mode of investing. Investors can change their investing from manual to automatic mode or vice versa. Therefore, we employ an OLS regression model at investor-bid level.

$$\text{Switch}\{G, A, M\}_{i,t} = \beta_0 + \beta_1 \text{Portfolio Performance}_{i,t-1} + \beta_2 \text{Loan}_{i,\gamma} + \beta_4 \text{Borrower}_{i,\gamma} + \delta_i + D_i + \varepsilon_{i,t} \quad (2.4)$$

[21] Panel Probit or Logit model is better than a linear probability model but is not used due to the sample size we have. The data is huge so relying on Probit or Logit will take a lot of time to get appropriate results.

Where subscript *i* indicates the investor and subscript *t* indicates the bid attempt for investor *i*. $Switch\{G, A, M\}_{i,t}$ is split into three dummy variables. The first binary variable indicates *General Switching* that will equal to one if a lender either switch to manual or automatic mode, 0 otherwise. The second variable is *Switching to Automatic*, and it equals to one if investors switch to automatic, 0 otherwise. The third variable is *Switching to Manual*, and it is a dummy variable that equals to one if investors switch to the self-directed mode, 0 otherwise. The remaining variables are the same as in the previous model (Eq 2.3).

2.5. Empirical analysis

We start our analysis by reporting correlations between investors' automated tools and characteristics of investors, loans, and borrowers in Table 2.3. Next, Table 2.4 presents the relationship between portfolio performance and the switching mode of investing. Furthermore, table 2.5 adds the experience factor that is missing in the previous model. Finally, Table 2.6 investigates the impact of switching on decision-making.

2.5.1. Usage of automated biddings

Table 2.3 reports the effects of equation 2.3. The first column controls for loan characteristics, column 2 adds borrower characteristics to the previous model, while column 3 removes all characteristics and controls for loan fixed effects.

Table 2.3: Automatic bidding and performance

	(1)	(2)	(3)
	Loan	**Borrower**	**Investor**
Portfolio Performance$_{t-1}$	38.287***	37.966***	2.595***
	(0.022)	(0.022)	(0.002)
Log (Maturity)$_t$	8.925***	9.242***	
	(0.000)	(0.000)	
Credit Risky$_t$	-37.302***	-37.204***	
	(0.001)	(0.001)	
Interest Rate$_t$	-2.677***	-2.628***	
	(0.000)	(0.000)	
Log (Monthly Income)$_t$		-0.201***	
		(0.000)	
Married$_t$		-0.629***	
		(0.000)	
High Education$_t$		-0.086***	
		(0.000)	
Male$_t$		-0.035***	
		(0.000)	
Investor Fixed Effect	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes
Loan Fixed Effect	No	No	Yes

Observations	72,766,206	71,715,050	72,745,012
Adjusted R2	0.560	0.560	0.941

Notes: This table examines performance and relying on Automatic Bidding. Columns 1-3 use *Auto Bidding* as the dependent variable. Column (1) reports the loan and investor characteristics that might influence using an automatic bid. Column (2) controls the borrower, loan, and investor characteristics, and Column (3) only controls for investor characteristics. Portfolio Performance is weighted by investor's bid amounts and is a measurement for portfolio performance for each investor at time t – 1. Log (Maturity) is the logarithm of one plus the maturity of the loan. Credit Risky is a dummy where 1 = HR or E loan risk, 0 = otherwise. Interest Rate (%) is the interest rate of the loan. Log (Monthly Income) is the logarithm of one plus borrowers' monthly income. Married is a dummy for borrowers where 1 = Married, 0 = otherwise. High Education is a dummy for borrowers where 1 = Masters or Above, 0 = otherwise. Male is a dummy for borrowers where 1 = Male, 0 = Female. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

Before addressing our main question about changing mode of investing, we would like to present the correlations between automatic bidding and characteristics of investors, loans, and borrowers. The estimates suggest that $\text{Portfolio Performance}_{t-1}$ in the three models of Table 2.3 takes a positive sign indicating that those who perform well in the market are more likely to invest using the automated service than self-directed biddings. The size of the coefficient in column 1 is considered significantly big compared to existing studies.[22] For example, the estimates suggest in the first column that a one-unit increase in weighted average interest rate per one unit of risk increases the usage of automated biddings by 38 percentage points. Moreover, when we control for Loan FE in addition to investor and time FE in column 3, the performance of investors appears to be weakened but still has the same positive sign. However, the significance of portfolio performance has dropped to 2.5 percentage points. Perhaps when we include loan and investor fixed effects to control for unobserved heterogeneity across listings and lenders, the efficiency of this tool will be weakened due to the presence of many factors. Nevertheless, this does not take away the relation between portfolio performance and using automation, as those who rely on the automated toolbox still perform better than self-directed bidders.

Regarding loan characteristics in column 1, our results show that individuals who rely on automation invest in higher maturity loans. This is evidenced by the positive significance on Log (Maturity)_t. Particularly, a 100% change in the maturity of the loan increase the chance of using the automated biddings by 9.2 percentage points. This can be explained by the fact that automated services prefer long-term projects (see, e.g., Menkveld, 2013).[23] Second, the auto-toolbox is less likely to be associated with more profitable and riskier loans, evidenced by the negative significance of Credit Risky_t and Interest Rate_t. Mainly, it might not be

[22] See for example Rossi and Utkus (2020), where the size of the coefficients ranges between 0 and 1 after adopting the robo advising service.
[23] In their paper, they report that the majority of HFT trades are considered passive trades (by 78.1%).

preferable for some individuals since investors are not risk-averse (see, e.g., Parrino et al., 2005).[24]

Although people cannot know what machines are doing, individuals still appreciate the blindness of the algorithmic process (Logg et al., 2019). In this paper, investors have no access to what loan the automated service bids on. The lender only sets the bid amount, interest rate, and maturity of the loan. The rest is all done by machines. Therefore, in column 2, we add the borrower characteristics to the model. Our results show that automated biddings do not discriminate against specific borrowers like a manual bid attempted by a human would. In particular, females, unmarried, and less financially literate borrowers are likely to get funded by the auto-toolbox. This is because human investors would prefer to fund financially literate borrowers (e.g., Caglayan et al., 2020; Campbell, 2006), married, and are males (e.g., Chen et al., 2020). Additionally, Human investors would usually show high uncertainty when evaluating an application made by a female (e.g., Duan et al., 2020). Overall, this all relates to human investors being prone to displaying biases (see, e.g., Foerster et al., 2017). In a more recent and related study in P2P lending D'Acunto, Ghosh, et al. (2021) provided extensive evidence on how investors in microlending markets face significant losses when they discriminate against a particular group of borrowers.

2.5.2. Determinants of switching

This analysis not only sheds light on the usage of automation but is extended by investigating the importance of switching or changing the mode of investing. Remarkably, some investors can switch between bidding modes and change to automatic or manual when lending on *Renrendai.com*. Therefore, we drop users who rely on one bidding mode and consider hybrid users only to investigate switching. Table 2.4 displays the effects of equation 2.4.

Table 2.4: Switching mode of bidding

	(1)	(2)	(3)
	General Switching	**Auto Switching**	**Manual Switching**
Portfolio Performance$_{t-1}$	-1.005***	-7.191***	6.186***
	(0.002)	(0.005)	(0.005)
Log (Maturity)$_t$	-2.831***	0.191***	-3.022***
	(0.000)	(0.000)	(0.000)
Credit Risky$_t$	3.205***	-4.910***	8.114***
	(0.001)	(0.000)	(0.001)

[24] We have also presented evidence of the likeness of investors relying on less profitable and lower risky loans when they use automatic biddings in the Online Appendix of Table TA2-7.

Interest Rate_t	0.505***	0.425***	0.080***
	(0.000)	(0.000)	(0.000)
$\text{Log (Monthly Income)}_t$	-0.084***	0.075***	-0.159***
	(0.000)	(0.000)	(0.000)
Married_t	0.102***	0.055***	0.047***
	(0.000)	(0.000)	(0.000)
High Education_t	-0.049**	0.023	-0.072***
	(0.000)	(0.000)	(0.000)
Male_t	0.038***	-0.077***	0.115***
	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes
Observations	23,358,551	23,358,551	23,358,551
Adjusted R2	0.094	0.045	0.054

Notes: This table examines the relationship between portfolio performance and the decision to switch. Columns 1-3 used *General Switch, Switch to Automatic, and Switch to Manual* as dependent variables. Portfolio Performance is weighted by investor's bid amounts and is a measurement for portfolio performance for each investor at time t – 1. Log (Maturity) is the logarithm of one plus the maturity of the loan. Credit Risky is a dummy where 1 = HR or E loan risk, 0 = otherwise. Interest Rate (%) is the interest rate of the loan. Log (Monthly Income) is the logarithm of one plus borrowers' monthly income. Married is a dummy for borrowers where 1 = Married, 0 = otherwise. High Education is a dummy for borrowers where 1 = Masters or Above, 0 = otherwise. Male is a dummy for borrowers where 1 = Male, 0 = Female. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

Column 1 shows that investors are likely to make a general switch when they have a lower portfolio performance. For example, a decrease in the weighted interest rate per one unit of risk of $\text{Portfolio Performance}_{t-1}$ increases the probability of changing the way lenders bid by one percentage point. This means that when investors underperform, they want to do something and change their behaviour because they are not satisfied with their current performance. However, this is a general switch, and it does not determine exactly which direction investors want to follow. To further investigate switching behaviour, we split switching into two indicators: switching to automatic and switching to manual. This can help us dig deeper into the argument and investigate how past portfolio performance impacts users' decision to switch to an automated investing tool.

Investors with poor portfolio performance are likely to switch to automatic. This is shown in column 2 by the negative significance on $\text{Portfolio Performance}_{t-1}$ where if the performance decreases by interest rate per one unit of risk, it increases the chances of switching to the automated toolbox by 7.1 percentage points. This infers that investor believe that switching to the automated mode makes them better performers. In a related study, Rossi and Utkus (2020) found out that investors that have a lower return and higher risk are the ones that sign up for robo-advising by 0.05 and 0.16 percentage points, respectively. Previous works (e.g., Capponi et al., 2019; D'Acunto, Prabhala, et al., 2019; D'Hondt et al., 2020; Reher and Sun, 2019) have also shown that automated financial tools can enhance the portfolio performance of individuals. Contrarily, good-performing investors prefer to rely on themselves in the manual mode. In column 3, the results report a positive coefficient on $\text{Portfolio Performance}_{t-1}$where an increase in portfolio performance leads to a 6.1 percentage point increase in switching to manual mode. This infers that good-performing users prefer to rely on themselves in the manual mode after achieving a good and consistent performance in the automated mode. One might argue that individuals want to get involved in riskier loans since the auto toolbox invests in risk-free loans.[25] In order to further investigate this, In the Online Appendix of Table TA2-10, we split portfolio performance into risk and returns. The estimates suggest that less risky investors switch to the manual mode, whereas investors who are considered riskier prefer to switch to the automated mode.

Foerster et al. (2017) found that adopting robo-advice or portfolio optimizing tools can mitigate under diversification. In a more recent investigation, Loos et al. (2020) showed that investors who use robo-advising are likely to mitigate under diversification by 11.7 percentage points when controlling for both time and investor fixed effects. Additionally, D'Acunto, Prabhala, et al. (2019) find that adopting robo-advice is beneficial for some investors since it increases their portfolios' diversification, hence reducing portfolio volatility. Simultaneously, the robo-advisor does not improve the performance or volatility of the portfolios of already-diversified investors. On average, they find that investors had a better-diversified portfolio by 0.16 units. Mainly, this is about 1.3% of the median number of stocks investors had in their portfolios before using the automated tool. In our study, we do not have a diversification factor that will reflect portfolio performance. However, we created a proxy that controls the cumulative number of unique successful investments that enter an individual's portfolio. Therefore, we repeat the analysis of Table 2.4 using a new measurement that measures portfolio performance. In the Online Appendix of Table TA2.11, we use the Log $(\text{Successful Investments})_{t-1}$, and we find consistent results to those shown in Table 2.4. We find that a 100% change in Log $(\text{Successful Investments})_{t-1}$ increases the probability of changing to the automated mode by 3.59 percentage points. At the same time, individuals who find success by themselves tend to rely on the manual mode by 0.55 percentage points.

[25] In the Online Appendix of Table TA2-8, we repeat the analysis with dropping investors that have attempted less than 10 bids assuming that in the first 10 attempts, there will be no switching happening. Moreover, in Table TA2-9, we control for Loan fixed effects in order to show the robustness of our results. In both robustness checks, our results show consistency with those shown in Table 2.4 for automatic and manual switching.

Our estimates suggest that higher maturity and lower risky loans are associated with an automated switch for loan characteristics. In comparison, lower maturity and higher risky investments are associated with a manual switch. Additionally, switching to automatic is more likely to invest in a higher interest investment than when the individual was bidding in the manual mode. This means that after a spell of investment mistakes in the manual mode, the investor switches to automatic and realizes a higher return at the time of switch than when he was in the manual mode. Moreover, for borrower characteristics in columns (2) and (3), we find that the more the loan is associated with males, the less likely it will be an automated switch. Also, low monthly income and highly educated borrowers are associated with a manual switch. Finally, married borrowers are associated with both a manual and an automatic switch. However, the significance is weaker for the automated one.

2.5.3. Experience and switching

Next, studies have shown that experience also directly impacts investor behaviour over time (e.g., Hoffmann et al., 2015). Therefore, the upcoming model controls for individual investor experience. We run a linear probability model. To capture experience, we measure it as the active days spent on the market. Other studies have used time to measure experience as time spent in years (e.g., Chernenko et al., 2016) or calendar time and account tenure (e.g., Nicolosi et al., 2009). columns 1 and 2 measures experience using investors profile age and is the active time spent on the market, while columns 3 and 4 measures experience as the number of bids attempted by investors.

Table 2.5: Experience and switching

	(1)	(2)	(3)	(4)
	Auto Switching	**Manual Switching**	**Auto Switching**	**Manual Switching**
Portfolio Performance$_{t-1}$	-3.264***	5.465***	-3.254***	5.481***
	(0.010)	(0.009)	(0.010)	(0.009)
Log (Profile Age)$_{t-1}$	1.216***	-0.103**	1.215***	-0.096**
	(0.001)	(0.000)	(0.001)	(0.000)
Portfolio Performance$_{t-1}$* Log (Profile Age)$_{t-1}$	-8.911***	4.557***	-8.902***	4.517***
	(0.003)	(0.003)	(0.003)	(0.003)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Loan Fixed Effect	Yes	Yes	Yes	Yes
Day of Bid Fixed Effect	No	No	Yes	Yes
Hour of Bid Fixed Effect	No	No	Yes	Yes
Observations	23,335,117	23,335,117	23,335,117	23,335,117
Adjusted R2	0.123	0.301	0.123	0.300

Notes: This table aims to control for experience in the model and see its impact on switching—columns (1) and (3) use *Switch to Automatic* as the dependant variable. Columns (2) and (4) use *Switch to Manual* as a dependant variable Portfolio Performance is weighted by investor's bid amounts and is a measurement for portfolio performance for each investor at time t – 1. Log (Profile Age) is the logarithm of one plus the number of active days spent by an investor on the market. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

To detect experienced investors, we inspect the coefficient that is associated with $\text{Log (Profile Age)}_{t-1}$. Table 2.5 shows that experienced investors are likely to switch to an automated mode, whereas less experienced individuals prefer to make decisions independently. In column (1) $\text{Log (Profile Age)}_{t-1}$ has a positive coefficient which means that if the experience increases by 100%, the possibility of switching to automatic increases by 1.2 percentage points. This implies that individuals who join the platform do not trust the automated system directly because they have not used it yet. However, with time, the more they switch to the auto toolbox and see how effective it is, the more they trust it. Castelo et al. (2019) show that humans reduce algorithmic aversion once they rely on algorithms. Also, automated bidding being associated with better performance is an excellent example of why investors on *Renrendai.com* increase the level of relying on the auto bidding toolbox more frequently from one year to the other. However, column (2) reports a negative coefficient on $\text{Log (Profile Age)}_{t-1}$, which means a 100% increase in active time spent on the market decreases the probability of switching to manual mode by 0.1 percentage points. The interaction term between performance and experience suggests that investors who are more experienced but have lower portfolio performance are more likely to change their investing mode to the automated one. Whereas more experienced and better-performing lenders are likely to stay investing in the self-directed mode. For the interaction terms between portfolio performance and active time, the results of the table show that those with higher experience and lower portfolio performance are likely to switch to the automated mode. However, investors with a high level of experience and have high portfolio performance prefer switching to the manual mode.

We repeat our analysis in columns 3 and 4 and find consistency with those in columns 1 and 2. We now control for additional time fixed effects such as the week, day, and hour of the bid attempted. Notably, it is critical to control for the heterogeneity of investors during specific times since investors tend to change their behaviour during certain times. The estimates suggest similar results to those found in columns 1 and 2. Overall, one might argue that individuals changed their behaviour and switched to automatic to reduce their risk-taking since the automated mode invests in safe investments. In support of this evidence, existing works have shown that experienced individuals are likely to be associated with less risk-taking (e.g., Shefrin, 2003) and realize lower returns as they gain experience (e.g., Chiang et al., 2011). To further prove this point, In the Online Appendix of Table TA2.12, we find consistent results with those reported in Table 2.5. The difference between the two tables is that in Table TA2.12, we control for another measurement for portfolio performance. We look at $\text{Log}\,(\text{Successful Investments})_{t-1}$ and it is the logarithm of one plus the number of successful investments that lenders have in their portfolios. We find out that underperforming investors, or those with a lower number of successful investments in their portfolio, switch to the automated mode, whereas those who perform well (have more successful investments) are likely to switch to the manual mode.

2.5.4. Robustness check

Having investigated portfolio performance and switching in the previous models, we inspect the influence of switching on investors' decision-making. Although there are investors who face algorithm aversion when things go the wrong way (Dietvorst et al., 2018), evidence-based algorithms have repeatedly proved that they make better decisions than humans. Therefore, using the fixed effect panel approach, we estimate the following:

$$\begin{aligned}\text{Decision}\{\text{P, P, R}\}_{\text{i,j,t}} = {} & \beta_0 + \beta_1 \text{Switch to Automatic}_{\text{i,j,t}} + \beta_2 \text{Switch to Manual}_{\text{i,j,t}} \\ & + \beta_3 \log\,(\text{Days Since Last Decision})_{\text{i,j,t}} + \beta_4 \text{Loan}_{\text{i,}\gamma} \\ & + \beta_5 \text{Borrower}_{\text{i,}\gamma} + \delta_{\text{i}} + \text{D}_{\text{i}} + \varepsilon_{\text{i,t}}\end{aligned} \tag{2.5}$$

Where the subscript *i* indicates the investor, subscript *j* indicates the loan, and subscript *t* indicates the bid attempt. $Decision_{i,j,t}$ is an indicator for decision-making and is split into three indicators. The first indicator is called *Decision Performance* and is measured as follows. Let $LP_j = Interest\,/_{Risk}$ where LP_j is loan performance, *Interest* is the interest rate of the loan and *Risk* is the risk score of the loan. So, loan performance represents the risk-adjusted returns of a loan. In order to compute the decision performance of investors, we do the following:

$$\text{Decision Performance}_{\text{i,j,t}} = \text{LP}_{\text{j,i,t}} - \overline{\text{Performance}^{\text{w}}}_{\text{j,t}-1} \tag{2.6}$$

Where $Decision\ Performance_{i,j,t}$ is the difference between loan performance at time t (based on return and risk) and investors weighted portfolio performance at time *t-1***.** Portfolio performance is described in sub-section 2.4.1. Then, to decide the financial outcome (acceptable or suboptimal), we do the following:

$$\text{Decision Performance}_{\text{i,j,t}} = \begin{cases}\text{Suboptimal Decision, if } \text{LP}_{\text{j,i,t}} - \overline{\text{Performance}^{\text{w}}}_{\text{j,t}-1} < 0 \\ \text{Acceptable Decision, if } \text{LP}_{\text{j,i,t}} - \overline{\text{Performance}^{\text{w}}}_{\text{j,t}-1} \geq 0\end{cases} \tag{2.7}$$

The efficiency of the decision will be computed by the difference between loan performance and investor weighted average portfolio performance. The same scenario will happen for *Decision Profitability* and *Decision Riskiness*. *Decision Profitability* will be the difference between the loan interest rate at time t, and the investor weighted average returns at time *t-1*. *Decision Riskiness* will be the difference between loan risk at time t and investors weighted average risk at time *t-1*.

For the explanatory variables, Switch $Auto_{i,j,t}$ and Switch $Manual_{i,j,t}$ are binary variables that indicate whether users switch to automatic or to manual. Log(Days Since Last $Decision)_{i,j,t}$ is measured by the logarithm of one plus the days spent between one decision at time ***t*** and the previous decision at time *t - 1*.δ_i *and* D_i are investors and hour of bid fixed effects.

Table 2.6 displays the effects of equation 2.5. column 1 uses *Decision Performance* as the dependent variable. Columns 2 and 3 use *Decision Profitability* and *Decision Riskiness*, respectively for extra checks. This test aims to investigate further the relationship between switching to automatic or manual and decision making.

Table 2.6: Decisions when switching

	(1)	(2)	(3)
	Decision Performance	**Decision Profitability**	**Decision Riskiness**
Switch to $Automatic_t$	0.476***	4.906***	-5.950***
	(0.000)	(0.001)	(0.002)
Switch to $Manual_t$	-0.626***	6.523***	44.815***
	(0.000)	(0.001)	(0.003)
Log $(Maturity)_t$	1.188***	59.983***	-36.274***
	(0.000)	(0.001)	(0.002)
Log (Monthly $Income)_t$	0.082***	-13.740***	-7.925***
	(0.000)	(0.001)	(0.000)
$Married_t$	-0.063***	-0.272***	1.251***
	(0.000)	(0.000)	(0.000)
High $Education_t$	0.063***	-2.210***	1.284***
	(0.000)	(0.000)	(0.000)
$Male_t$	-0.195***	0.215**	5.134***
	(0.000)	(0.001)	(0.001)
Log (Days Since Last $Decision)_t$	-0.049***	-1.433***	0.514***
	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes
Loan Fixed Effect	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes
Observations	23,358,542	23,428,673	23,428,673
Adjusted R2	0.070	0.424	0.680

Notes: This table shows the relationship between switching and decision-making. Columns (1-3) take different measurements of Decisions as a dependant variable. Column (1) is *Decision Performance*, Columns (2) is *Decision Profitability*, and column (3) is *Decision Riskiness*. Decision Performance is a measurement for decision making and is the difference between loan performance at time t and investor's previous portfolio performance. Decision Profitability is a measurement for decision making and is the difference between loan return at time t and investor's previous profitability. Decision Riskiness is a measurement for risk taking and is the difference between loan risk at time t and investor's previous risk performance. Switch to Automatic is a dummy variable where 1 = switch to automatic investing, 0 = otherwise. Switch to Manual is a dummy variable where 1 = switch to self-directed investing, 0 = otherwise. Log (Maturity) is the logarithm of one plus the maturity of the loan. Credit Risky (1 = Yes) is a dummy where 1 = HR or E loan risk, 0 = otherwise. Interest Rate (%) is the interest rate of the loan. Log (Monthly Income) is the logarithm of one plus borrowers' monthly income. Married (1 = Yes) is a dummy for borrowers where 1 = Married, 0 = otherwise. High Education (1 = Yes) is a dummy for borrowers where 1 = Masters or Above, 0 = otherwise. Male (1 = Yes) is a dummy for borrowers where 1 = Male, 0 = Female. Log (Days Since Last Decision) is the logarithm of days spent since the last decision made by the investor. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are robust and clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

When we examine the effect of switching to automatic on investment decisions in column 1, we find out that investors make better investments than those who decide to stay in the manual mode. Our results suggest that switching to automatic increases the chances of making a better decision by 0.0047 units. This infers that when investors change their behaviour and adopt an automated tool, they are likely to invest in better loans compared to those that are found in their portfolios. One might suggest that because machines can outperform humans and are better at decision-making than humans (e.g., see Kleinberg et al., 2018) then machines are likely to perform better in P2P lending markets as well. Additionally, algorithmic advice lets humans make wiser decisions (Logg et al., 2019), explaining why services based on algorithms are better for decision-making. As for $\text{Switch to Manual}_t$, the investor is less likely to make a good investment decision by 0.006 units than those who stay bidding in the automated mode.

In column 2, when we examine how switching influences profitable decisions, we find out that $\text{Switch to Automatic}_t$ and $\text{Switch to Manual}_t$ can invest in profitable decisions. However, those switching to manual have more substantial significance, implying that they are likely to invest in loans that have higher returns than what is found in their current portfolios. This might be due to that a human investor might be less risk-averse than a machine. Column (3) supports this evidence, where our results show that investors in the manual mode make riskier decisions. This is inconsistent with Loos et al. (2020) who showed that after investors join robo-advising services, they are likely to increase their financial risk-taking.

For time spent between one decision and the other, we find that the fewer days spent between the previous and the current decision, the better the financial outcome will be. This is evident on $\text{Log (Days Since Last Decision)}_t$ coefficients in columns (1), (2), and (3). However, this finding is inconsistent with several studies (e.g., de Paola and Gioia, 2016; Diederich and Busemeyer, 2003) that discuss how fast decision-making results in lower financial decision-making outcomes.

In the Online Appendix of Table TA2.13, we control for loan fixed effects and find consistent results with those that are reported in Table 2.6. However, the only difference is in column 2. The estimates suggest that the more investors Switch to Manual$_t$, the less likely they will make a profitable decision. So, when controlling for investors heterogeneity, which considers all characteristics, investors who want to rely on themselves in the manual mode attempt less profitable decisions than those who stay in the automated mode. This is consistent with Table 4, which shows that both manual and automatic switching is linked to good returns where the difference is presented in the strength and significance level of the coefficients. Overall, this infers that switching to automatic will let investors make a better profitable decision when switching.

2.6. Conclusion

Recent technological developments changed lending and borrowing from a process that goes through banks to an easily accessible online process. P2P lending platforms are evolving by offering new services to their customers that can ease their lending/borrowing process. At the same time, P2P lending platforms are taking new directions with respect to the services that they provide. For example, one of the popular tools that these platforms are offering is robo-advising. Investors seem to be interested in these automated tools due to several reasons such as (i) saving time, (ii) easy to use, (iii) and is considered consistent. A similar tool is provided for customers on Renrendai.com platform and is called the auto-bidding tool. In this paper, we are interested in investigating how portfolio performance affects investors' decision to switch to an automated toolbox.

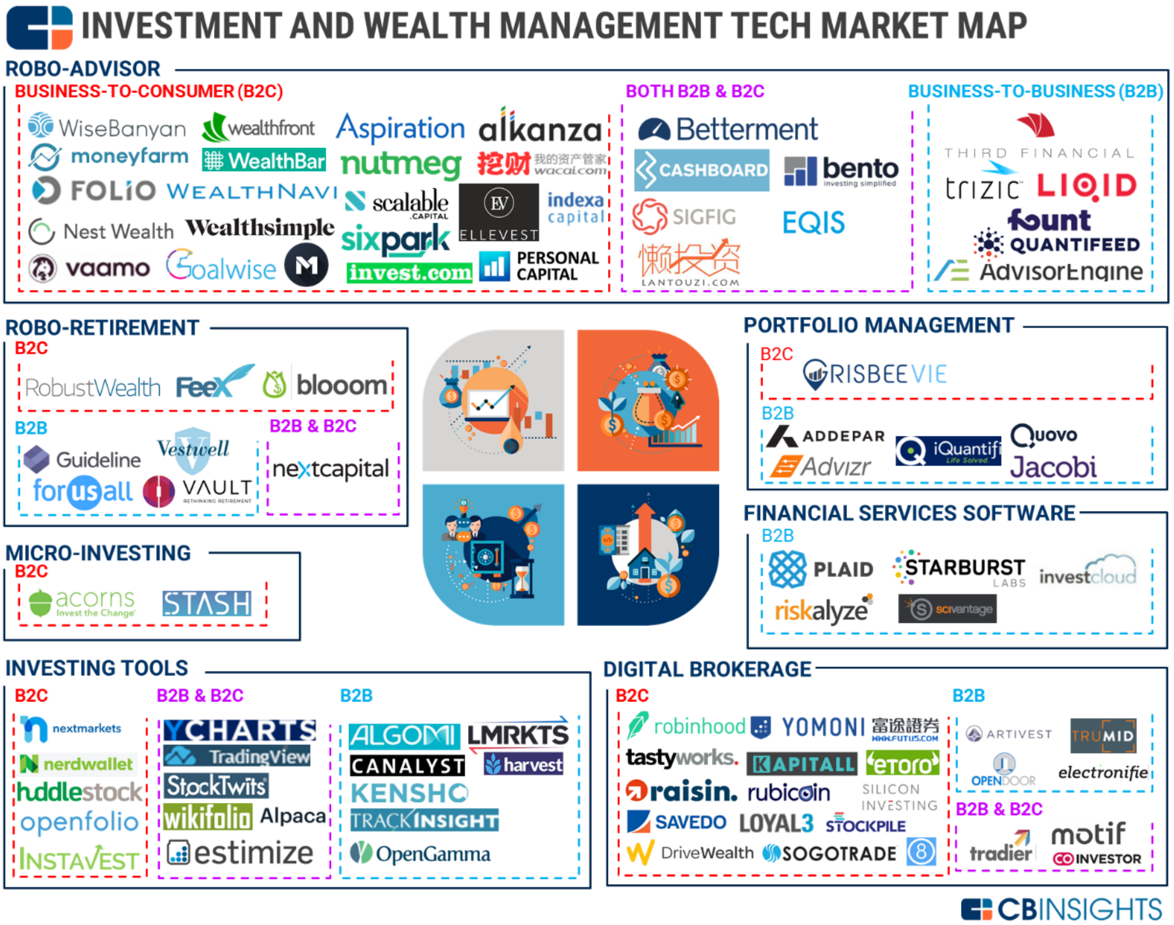
We start by investigating the correlations between automatic biddings and characteristics of investors, loans, and borrowers. Since borrower characteristics are not visible for investors when using the automated bidding tool, this will reveal which characteristics the auto-toolbox is correlated with the most. Then we reduce our sample and keep investors that use the hybrid investing method. The hybrid users rely on both automatic and manual biddings. This can help us investigate the relationship between portfolio performance and switching. Additionally, we control investors' experience to see whether experience is a primary factor in switching to automatic. Lastly, our investigation checks for the relation between decision making and switching.

This paper shows that good performer's investors are likely to rely on automatic bidding more than self-directed bidding. It is because the auto toolbox is associated with better performance. Furthermore, the automated toolbox discriminates less against unmarried, female, and less financially literate borrowers. When investigating switching, the results of hybrid investors who switch from one mode to another show that poor performers are likely to switch to automatic mode. However, good-performing individuals prefer to rely on themselves when making financial decisions.

Additionally, with experience and as individuals use the automated tool, they are more likely to switch to automatic. Moreover, our results report that investors make better decisions when switching to automatic. Lastly, investors who spend less time between one decision and the other result in a better financial outcome than those who spend longer days.

Online Appendix A

Figure FA2.1.1: Popularity of automated financial tools



Source: CBINSIGHTS

Notes: This figure shows the popularity of automation in finance. This is a small number of automated services that companies have been providing for their clients recently. This figure shows some leading companies relying on these tools, such as robo-advising and robo-retirement. All these companies are proposing a different framework and model to help individuals make better financial decisions, such as investment portfolios, lending decisions, or retirement decisions.

Table TA.2.7: Benefits of automatic bidding

	(1)	(2)
	Returns	**Risk**
Automatic Bidding (1 = Auto)	-53.574***	-13.060***
	(0.092)	(0.026)
Log (Maturity)	52.331***	-4.648***
	(0.055)	(0.013)
Log (Monthly Income)	-0.403***	0.127***
	(0.009)	(0.002)
Married (1 = Yes)	-0.317***	0.188***
	(0.015)	(0.003)
High Education (1 = Yes)	-2.208***	0.346***
	(0.044)	(0.008)
Gender (1 = Male)	-0.517***	0.119***
	(0.013)	(0.002)
Investor Fixed Effect	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes
Observations	71,715,050	71,715,050
Adjusted R2	0.699	0.312

Notes: This table shows the relationship between automatic biddings and the performance of the loan. Columns (1-2) take different measurements of Performance. Column (1) is Return of Loan, and Column (2) is Risk Score of Loan. Return and is measured by the Interest Rate of the Loan. Risk and is measured by the logarithm of one plus the risk score of the loan. Automatic Bidding is a dummy variable where 1 = Automatic Bid, 0 = otherwise. The remaining variables are the same as the ones in Table 2.3. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are robust and clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

Table TA2.8: Switching

	(1)	(2)	(3)
	General Switching	**Auto Switching**	**Manual Switching**
Portfolio Performance$_{t-1}$	-1.013***	-7.193***	6.180***
	(0.002)	(0.005)	(0.005)
Log (Maturity)$_t$	-2.832***	0.188***	-3.020***
	(0.000)	(0.000)	(0.000)
Credit Risky$_t$	3.212***	-4.904***	8.117***
	(0.001)	(0.000)	(0.001)
Interest Rate$_t$	0.506***	0.426***	0.080***
	(0.000)	(0.000)	(0.000)
Log (Monthly Income)$_t$	-0.085***	0.074***	-0.159***
	(0.000)	(0.000)	(0.000)
Married$_t$	0.102***	0.054***	0.047***
	(0.000)	(0.000)	(0.000)
High Education$_t$	-0.048*	0.024	-0.072***
	(0.000)	(0.000)	(0.000)
Male$_t$	0.038***	-0.077***	0.115***
	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes
Observations	23,350,175	23,350,175	23,350,175
Adjusted R2	0.093	0.045	0.054

Notes: This table examines the relationship between portfolio performance and the decision to switch. This table drops investors who made less than ten bids assuming that there will be no switching happening in the first ten bids attempted by investors. All variables remaining are the same as the ones in Table 2.4. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

Table TA2.9: Switching (Loan FE)

	(1)	(2)	(3)
	General Switching	**Auto Switching**	**Manual Switching**
Portfolio Performance$_{t-1}$	-2.934***	-14.835***	11.902***
	(0.003)	(0.010)	(0.008)
Investor Fixed Effect	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes
Loan Fixed Effect	Yes	Yes	Yes
Observations	23,465,116	23,465,116	23,465,116
Adjusted R2	0.161	0.092	0.276

Notes: This table examines the relationship between portfolio performance and switching. In this table, we control for loan fixed effects to control for investor heterogeneity. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

Table TA2.10: Risk, returns, and switching

	(1)	(2)	(3)
	General Switching	**Auto Switching**	**Manual Switching**
Log (Risk)$_{t-1}$	0.011***	0.055***	-0.044***
	(0.000)	(0.000)	(0.000)
Returns$_{t-1}$	0.834***	0.085***	0.750***
	(0.000)	(0.000)	(0.000)
Log (Maturity)$_t$	-2.706***	0.353***	-3.059***
	(0.000)	(0.000)	(0.000)
Credit Risky$_t$	3.121***	-5.102***	8.222***
	(0.001)	(0.000)	(0.001)
Interest Rate$_t$	0.379***	0.351***	0.028***
	(0.000)	(0.000)	(0.000)
Log (Monthly Income)$_t$	-0.075***	0.074***	-0.149***
	(0.000)	(0.000)	(0.000)
Married$_t$	0.090***	0.046***	0.044***
	(0.000)	(0.000)	(0.000)
High Education$_t$	-0.038	0.030	-0.068***
	(0.000)	(0.000)	(0.000)
Male$_t$	0.033***	-0.081***	0.114***
	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes
Observations	23,425,360	23,425,360	23,425,360
Adjusted R2	0.092	0.045	0.054

Notes: This table examines the relationship between portfolio performance indicators and the decision to switch. This table splits portfolio performance into risk and returns. All variables remaining are the same as the ones in Table 2.3. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

Table TA2.11: Portfolio performance proxy (Success)

	(1)	(2)	(3)
	General Switching	**Auto Switching**	**Manual Switching**
Log (Successful Investments)$_{t-1}$	-3.044***	-3.596***	0.552***
	(0.000)	(0.000)	(0.000)
Log (Maturity)$_t$	-2.557***	0.483***	-3.040***
	(0.000)	(0.000)	(0.000)
Credit Risky$_t$	2.697***	-5.336***	8.033***
	(0.001)	(0.000)	(0.001)
Interest Rate$_t$	0.517***	0.437***	0.080***
	(0.000)	(0.000)	(0.000)
Log (Monthly Income)$_t$	-0.093***	0.066***	-0.159***
	(0.000)	(0.000)	(0.000)
Married$_t$	0.089***	0.040***	0.048***
	(0.000)	(0.000)	(0.000)
High Education$_t$	-0.056**	0.013	-0.068***
	(0.000)	(0.000)	(0.000)
Male$_t$	0.036***	-0.079***	0.115***
	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes
Hour of Bid Fixed Effect	Yes	Yes	Yes
Observations	23,358,551	23,358,551	23,358,551
Adjusted R2	0.093	0.048	0.054

Notes: This table examines the relationship between portfolio performance and the decision to switch. Columns 1-3 used *General Switch, Switch to Automatic, and Switch to Manual* as dependent variables. The rest of the variables are the same as the ones used in Table 2.3. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

Table TA2.12: Experience and switching (Loan FE)

	(1)	(2)	(3)	(4)
	Auto Switching	**Manual Switching**	**Auto Switching**	**Manual Switching**
$\text{Log (Successful Investments)}_{t-1}$	-4.796***	3.614***	-4.792***	3.600***
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Log (Profile Age)}_{t-1}$	1.170***	-0.001	1.170***	0.002
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Log (Successful Investments)}_{t-1} * \text{Log (Profile Age)}_{t-1}$	0.367***	-0.364***	0.366***	-0.363***
	(0.000)	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Loan Fixed Effect	Yes	Yes	Yes	Yes
Day of Bid Fixed Effect	No	No	Yes	Yes
Hour of Bid Fixed Effect	No	No	Yes	Yes
Observations	23,532,001	23,532,001	23,532,001	23,532,001
Adjusted R2	0.127	0.301	0.127	0.300

Notes: This table controls for experienced investors that switch. Columns (1) and (3) has Switch to Auto as a dependant variable. Columns (2) and (4) has Switch to Manual as a dependant variable. Log (Profile Age) is investors' profile age and is the logarithm of one plus the number of active days investors spend on the platform. $\text{Log (Successful Investments)}_{t-1} * \text{Log (Profile Age)}_{t-1}$ is an interaction term between portfolio performance and investor's profile age. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

Table TA2.13: Decision when switching (Loan FE)

	Decision Performance	Decision Profitability	Decision Riskiness
	(1)	(2)	(3)
Switch to Automatic$_t$	0.228***	4.527***	-1.268***
	(0.000)	(0.001)	(0.000)
Switch to Manual$_t$	-0.226***	-1.446***	1.462***
	(0.000)	(0.001)	(0.000)
Log (Days Since Last Decision)$_t$	-0.023***	-2.577***	-0.099***
	(0.000)	(0.000)	(0.000)
Investor Fixed Effects	Yes	Yes	Yes
Hour of Bid Fixed Effects	Yes	Yes	Yes
Loan Fixed Effects	Yes	Yes	Yes
Observations	23,465,116	23,535,344	23,532,000
Adjusted R2	0.938	0.903	0.871

Notes: This table examines the relationship between switching and decision-making. The only difference from table 2.6 is that we add loan fixed effects to the model. All remaining variables are the same as Table 6 **Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at individual and loan levels. Coefficients are multiplied by 100 for presentation purposes.

Table TA2.14: Variable's definition

Variable	Description
Auto Bidding	A binary variable that equals to 1 if the automated bidding tool attempted a bid, 0 otherwise.
General Switch	A binary variable that equals to 1 if investors switched to either manual or automated mode, 0 otherwise.
Switch to Automatic	A binary variable that equals to 1 if investors switched to an automated bidding mode, 0 otherwise.
Switch to Manual	A binary variable that equals to 1 if investors switched to a self-directed bidding mode, 0 otherwise.
Portfolio Performance	The portfolio performance of individuals and is measured by reward-to-risk ratio that is weighted by investors' amount of the bid.
Profile Age	Represents investor's profile age and is measured by the active time (in days) spent investing on the platform.
Successful Investments	The number of successful and unique investments that went into investors portfolio.
Maturity	The duration (in months) of a loan.
Credit Risky	A binary variable that equals 1 if the loan rating is HR or E loan risk, 0 = otherwise.
Interest Rate (%)	The interest rate earned from a loan.
Monthly Income	The monthly income of borrowers.
Married	A binary variable that equals to 1 if the borrower is married, 0 otherwise.
High Education	A binary variable that equals to 1 if borrowers have master's or Above degree, 0 = otherwise
Gender	A binary variable that equals to 1 if the borrower is a male, 0 otherwise.
Days Since Last Decision	The number of days spent between decisions.
Decision Performance	Decision Performance is a measurement for decision making and is the difference between loan performance at time t and investor's previous portfolio performance.
Decision Profitability	Decision Profitability is a measurement for decision making and is the difference between loan return at time t and investor's previous profitability.
Decision Riskiness	Decision Riskiness is a measurement for risk-taking and is the difference between loan risk at time t and investor's previous risk performance.
Returns	Returns is the interest rate offered on a loan.
Risk	Risk is the risk score and is explained in detail in section 2.4.2.

Notes: This table displays the definition of the variable.

Chapter 3. Funding Supply Shock and Loan Concentration.[26]

[26] In this chapter, we use material that is submitted to University of Birmingham for the assignment of Advanced Research Methods module and for the Annual Review.

3.1. Introduction

The concentration indices indicate the competitiveness of a certain area. Loan concentration is a new term that is used to describe the level of competitiveness for investing in a loan. It shows the level of interest that lenders display towards investing and can determine their power. The classic theory maintains that suppliers and customers compete for economic profits (Hui et al., 2019). A higher concentration of customers indicates the power of these individuals. When customers have more power, they can negotiate regular terms and turn them in their favor (Chen, 2008; Snyder, 1998; Stigler, 2010). Also, a concentrated customer base is often considered as an influential factor as it is believed to have a positive implication on the economies of scale and enhance operating efficiency. However, the level of concentration is subject to change with the introduction of financial regulations (see, e.g., Campello and Gao, 2017). This paper aims to test loan concentration indicators using an unanticipated financial regulation that made more funding available within a country.

Exiting works find that suppliers with a higher concentrated base are likely to hold assets that can be easily transferred into cash (Itzkowitz, 2013), maintain a lower leverage ratio (Banerjee et al., 2008), and reduce discretionary spending (Raman and Shahrur, 2008). Other literature argues that high customer concentration has a negative side, such as hurting supplier firms' profits (Murfin and Njoroge, 2015; Saboo et al., 2017), demanding lower prices, purchasing irregularly, and delaying payments (Herskovic et al., 2020).[27] More recent investigations explain the relationship between customer concentrations and firm profitability (e.g., Hui et al., 2019; Irvine et al., 2016; Patatoukas, 2012). In this study, we extend this literature by showing the importance of concentration in microlending markets.

The method in this study is to explore the response of Renrendai.com clients to a disruption event, which, in turn, affected the money flow in China. Specifically, the 2017 Chinese regulation is used as a trigger for more available funding. This regulation started in July of 2017. The reason behind this is that capital outflows became a growing source of concern for the Chinese government in 2017 as it tries to get the economy back on track and maintain currency stability without depleting the country's foreign exchange reserves, which fell to

[27] See also Elyasiani and Zhang (2018) and Chen (2014) where they show the relation between loan syndication and CEO's entrenchment and risk-taking incentives, respectively. Additionally, see Chen and Fan (2017) that studies the concentration of loan syndicates and the impact that CEO's debt holdings that had on it. Also, see Lin et al (2018) where the authors study the impact of the private benefits of managers on loan syndication.

$3.052 trillion in November 2016, the lowest level in nearly six years.[28] Therefore, we want to inspect how investors and borrowers reacted to such regulation that caused an increase in the spending power of investors in China.

Our results provide evidence on the influence of the 2017 announcement on *Renrendai.com*. First, the estimates suggest that after the financial regulation, investors became less interested in investing in loans where there was a decrease in the concentration of loans. In particular, borrowers decreased the interest rates offered for loans, resulting in higher concentration levels in more profitable loans. Moreover, this regulation had a negative impact on loan size. Borrowers decreased the requested amounts on loans, which will send positive signals to investors regarding the repayment of the funds. Finally, the repayment duration was increased, inferring that borrowers took advantage of the situation by decreasing their monthly repayment amounts. Our results are robust to "placebo" and different statistical tests.

Our paper contributes to several strands of literature in finance and economics. First, it relates the determinants of lending interest rates literature in P2P markets. Existing studies have found that borrower characteristics can significantly determine the interest rate offered on loans. These characteristics are discussed concerning credit score (e.g., Kgoroeadira et al., 2019; Michels, 2012), historical appearance (e.g., Ding et al., 2019), and pricing mechanism (e.g., Wei and Lin, 2017) [29]. Other works (e.g., Cheng et al., 2020) have shed light on the impact of information contagion that resulted from scandals on P2P lending interest rates. While these studies often emphasize the vital characteristics determining loan interest rates, there has been little evidence on the impact of financial regulations in determining the rates in online lending platforms.

Second, we contribute to the growing literature on the importance of concentration levels. Several works (e.g., Cen et al., 2016; Huang et al., 2016; Irvine et al., 2016; Patatoukas, 2012) have shown that customer concentration is related to higher performance. This increase in profitability originating from higher concentration levels has been transferred to investors by generating higher abnormal returns (e.g., Grullon et al., 2019). These studies have been investigated at the firm-industry level. Our paper relates to this strand of literature by showing the relationship between loan concentration and profitability at the loan level.

[28] See "China's new rules on yuan transfers are not capital controls: Xinhua (Reuters, January 02, 2017) (Available at: https://www.reuters.com/article/us-china-yuan-idUSKBN14M032), accessed on April 24, 2021.
[29] See also Larrimore et al. (2011) for usage of loan; Pope and Sydnor (2011) for discrimination; Lin et al. (2013) and Freedman and Jin (2017) for social capital.

Third, this paper is broadly related to the literature that focuses on the actual effects of money through its various transmission channels (see, e.g., Auclert, 2019; Garriga et al., 2017; Kuttner and Mosser, 2002; Mishkin, 1995). Existing works have proposed common causes in earlier works to explain the substantial money flow reported in empirical papers are linked to institutional reforms (e.g., Calvo, 1988), global shocks (e.g., Calvo et al., 1993), and domestic developments (e.g., Calvo et al., 1996). Later investigations often explain money supply through repurchase agreements, "repo" (e.g., Ranaldo et al., 2021), disruption events (e.g., Forbes and Warnock, 2021), and portfolio debt securities (e.g., Cerutti and Hong, 2021). Our empirical analysis is different as we see the transmission of the shock to a crowdfunding platform.

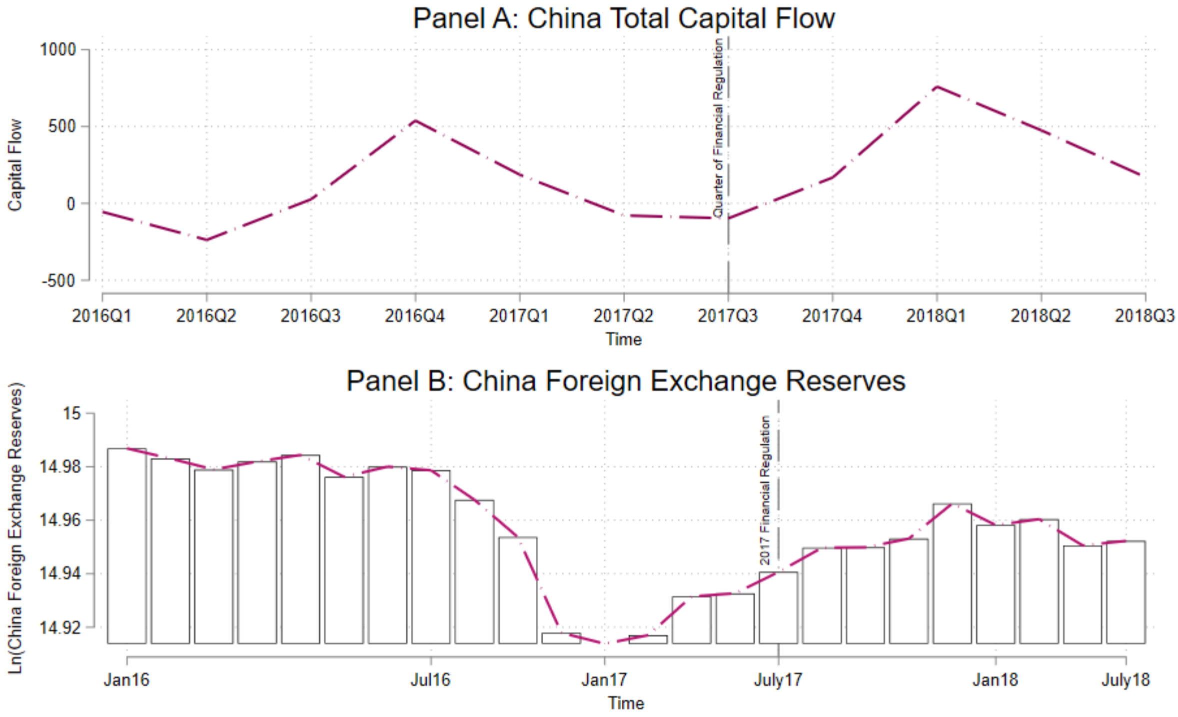
The rest of the paper is organized as follows: Section 3.2 talk introduces the 2017 financial announcement, section 3.3 talks about Renrendai.com platform, section 3.4 talks about the impact of the regulation on loan listing on Renrendai, section 3.5 introduces our data and sample collection, section 3.6 reviews the methodology and introduces the econometric model used, section 3.7 presents our main results, and section 3.8 concludes the paper.

3.2. The 2017 financial announcement

Our analysis focuses on the 2017 Chinese announcement, which sets new domestic and overseas currency transfers rules and develops new restrictions on purchasing foreign currencies, securities, and life insurance. On the 30th of December of 2016, the People's Bank of China (PBOC) announced that all financial institutions, starting from July 2017, are obliged to report any domestic and foreign cash transactions of more than RMB50,000 to the central bank. The previous amount that institutions used to report had a threshold of RMB200,000. At the same time, banks will have to report foreign transfers of $10,000 or more that individuals attempt. This announcement was followed by a separate announcement by the State Administration of Foreign Exchange (Safe). The regulator promised to intensify scrutiny of the use of the $50,000 annual quota by individuals to prevent it from being invested in restricted areas, such as foreign property and securities. On the 2nd of January, Reuters also reported that Bank of Shanghai and China Merchants Bank had begun to ask customers to promise when they applied online for foreign currency conversion that they would not buy foreign property, securities, life insurance, and other investment-style insurance products.[30]

[30] See "China's new rules on yuan transfers are not capital controls: Xinhua" (Reuters, January 02, 2017) (Available at: https://www.reuters.com/article/us-china-yuan-idUSKBN14M032), accessed on April 24, 2021.

Figure 3.1: China's Total Capital Flow and FX Reserves



Data Source: People's Bank of China | SAFE China

Note: This figure shows China's Foreign Exchange Reserve and Total Capital Flow from 2016 to 2018. In Panel A, the vertical axis on the left is the total capital flow. The grey dashed vertical line marks the quarter of the financial regulation (Q3 2017). In Panel B, the vertical axis on the left is the natural logarithm of the foreign exchange reserves (ln FX reserves). The grey dashed vertical line marks the month of the financial regulation.

The financial regulation was applied in July 2017 since capital outflows became a worrying issue for the Chinese government. Also, policymakers want to get their economy back and maintain currency stability without depleting the country's foreign exchange reserves, which fell to $3.052 trillion in November 2016. Panel A of Figure 3.1 shows the total capital flow, which started increasing immediately after the regulation. In particular, in 2018, reports claimed that China's cross-border capital flows reached a turning point in 2017 as they were balanced compared to the previous year's net outflows.[31] Panel B of Figure 3.1 shows how the FX exchange reserve increased gradually after the 2017 financial announcement.

[31] See "2017 marked a turning point for capital flows, China currency regulator says" (CNBC, January 17, 2018) (Available at: https://www.cnbc.com/2018/01/17/chinese-economy-china-capital-flows-stabilize-in-2017-fx-regulator.html), accessed on May 20, 2021.

3.3. Process on Renrendai.com platform

The process for investors is easier on Renrendai.com than for borrowers. First, bidders need to register with the forum and have their verification process completed. After they get verified, they start to search for suitable loans and to fund them. Lenders can either fully fund or partially fund a loan where the later decision is considered less risky for investors. If it is partially funded, this infers that the listing was unsuccessful, and borrowers should incur no fees. On the other hand, investors will contribute to a loan and incur the time and transactional costs due to the failure to fund that loan. In addition to that, if investors fully fund a loan and the loan fail (not fully funded), Renrendai guarantees that investors will be paid back in case that happens.[32] However, if a loan defaults, the investor bears all the risk in this case by losing the money spent on a particular loan.

As for borrowers, registering and getting verified is more challenging and can be done in two ways. The first way is based on an online authentication, and the other option is based on offline authentication. To start with the first option, to start looking for funds for their loans, borrowers need to submit their application form with their national identification number and provide additional personal details such as marital status, income, education, assets owned, certificates, and many more personal information.

In addition, borrowers would also need to specify the loan amount, the interest rate they would offer, the purpose of the loan, and the duration for repaying the entire fund.[33] After submitting all this personal information, the platform will evaluate the borrower's application and assign a credit rating that varies between high-risk (HR) and very safe (AA). After borrowers have been assigned a credit rating, Renrendai charges these borrowers an initial service fee. Within this context, investors will start to either wholly or partly fund the loan. If the target set has not been met, the loan will automatically fail and be labelled as a failure. Finally, after this lengthy procedure, borrowers still need to pay Renrendai.com some fees for service, certification, and management, which is considered another obstacle that borrowers usually face.

3.4. Impact of regulation on Renrendai listings

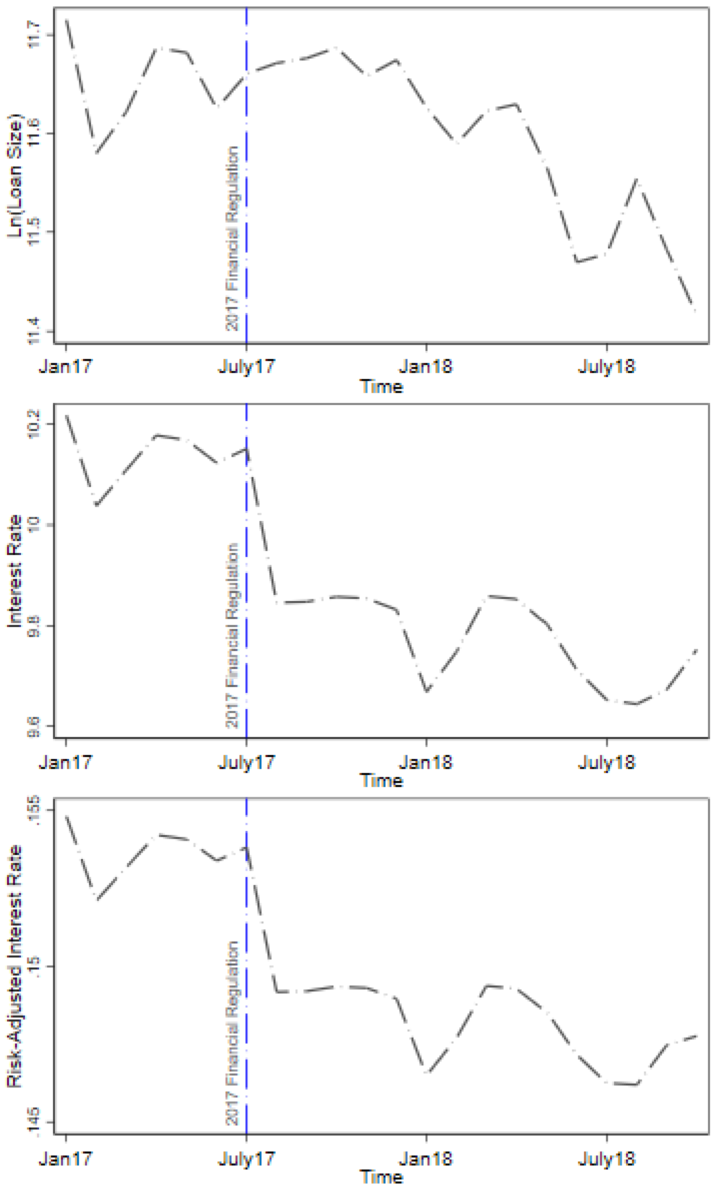
The process stayed the same on Renrendai.com. The borrowers still follow the same procedure when they want to sell a loan. However, the behaviour of borrowers in listing loans changed

[32] Renrendai reserve fund can cover possible defaults and late payments. This fund comes from the fees that the platform charges as service fees from customers. If the platform fails to collect back the loan, a collection agency will step in, and the money eventually collected will be put into the reserve fund.

[33] Interest rates can vary 6% to 24%. Maximum loan maturity is up to 3 years, and the loan amount that can be requested by borrowers vary between 3000RMB and 500,000RMB.

due to reacting to a financial shock. The Chinese authorities' announcement in July 2017 applied restrictions on overseas transfers, which means that the money will increase within the country, resulting in a change of borrowers' behaviour.

Figure 3.2: Impact of regulation on listings



Note: This figure shows the impact of the 2017 financial announcement on some loan characteristics. The vertical axis represents the logarithm of the loan amount, interest rates, and risk-adjusted interest rates. The blue dashed vertical line marks the month of the financial regulation.

Following the restrictions on overseas transactions, more money started flowing on the market, lowering the interest rates. In particular, figure 3.2 shows the impact of the 2017 announcement on several loan characteristics, including interest rates. We can observe that the financial shock was transferred to the P2P lending market, where borrowers on Renrendai.com reacted to the news by setting lower returns for investors when investing in a loan. Thus, this makes investing less exciting for lenders whereas more prosperous for borrowers. As a result, borrowers are offering lower interest rates, but they also decrease the loan amount to be funded. Before the regulation was announced, borrowers attracted investors with high loan amounts and high-interest rates. After the regulation, borrowers knew that investors' chances of investing in China increased, so they mitigated their efforts in attracting Chinese bidders.

3.5. Data description

The data collected for this study comes from Renrendai.com, one of China's most prominent and fastest-growing P2P lending platforms. From October 2010 to October 2018, 60,000 borrowers were registered on the platform, placing more than 200,000 listings. First, we collect information on loans and borrowers for each approved application. Second, we gather investor-level data based on each bid's timestamp, the amount invested in each loan, and the funding method for each loan. We obtain a sample of around 82,000 observations at a borrower-loan level by combining borrower- and loan-level data. Each loan application has financial information such as maturity, interest rate, the riskiness of the loan, and borrower characteristics such as monthly income, marital status, educational level, and gender of the borrower. Our exploration focuses on borrowers who are present on the platform before and post the 2017 financial regulation. The sample includes more than 37,000 borrowers, with 11,327 individuals during the regulation's pre-and post-period. This period covers the pre, during, and post-regulation, implying that these individuals posted more than one listing on the platform.

Table 3.1: Descriptive statistics, whole sample

	(1)	(2)	(3)	(4)	(5)
Variable	Mean	Std	P25	P50	P75
Interest Rate	0.11	0.03	0.10	0.10	0.11
Risk-Adjusted Interest Rate	0.16	0.37	0.14	0.15	0.15
Inflation Rate	0.02	0.00	0.02	0.02	0.02
Bid-Based-HHI	0.28	0.28	0.04	0.18	0.47
Investor-Based-HHI	0.27	0.27	0.03	0.17	0.45
Maturity	24.55	13.11	12.00	36.00	36.00
Loan Size	55204	60554	13200	43700	84100
Number of Unique Investors	66.99	107.57	10.00	26.00	76.00
Number of Bids on Loans	68.14	109.28	11.00	26.00	76.00
Debt-to-Income Ratio	0.33	0.95	0.09	0.19	0.35
Loan Status (1 = Closed)	0.45	0.50	0.00	0.00	1.00
Funding Type (1 = Manual)	0.29	0.45	0.00	0.00	1.00
Observations	82,986				

Notes: This table shows the Mean (1), Standard Deviation (2), and quartiles (3)-(5) of the following variables. Interest Rate is the interest rate of the loan. Risk-Adjusted Interest Rate is the interest rate that is adjusted by the risk of the loan. Bid-Based-HHI is a bid-number-based Herfindahl index (0,1] that shows the concentration of the loan. Investor-Based-HHI is a investor-based Herfindahl index (0,1] that shows the concentration of the loan. Total Number of Bids is the total number of bids attempted on loan. Maturity is the duration of the loan. Loan Size is the amount requested to fund a loan. Number of Unique Investors is the number of not repeated investors that are bidding on a loan. Debt-to-Income Ratio is the debt-to-income ratio for borrowers. Loan Status is a dummy variable that is equal to 1 if the loan was fully funded/closed, 0 otherwise. Funding Type is a dummy variable that equals 1 if human investors fully funded the loan, 0 otherwise.

Table 3.1 provides basic summary statistics for the total sample size of 37,000 borrowers. The sample includes borrowers who listed more than one loan on the market during their time. The average return offered on loans by borrowers is 11%. The Risk-Adjusted Interest Rate is 16% per one unit of risk. On Renrendai.com, borrowers are the ones that set the interest rates on loans. Therefore, to get financed faster, a borrower generally offers high interest in order to increase the chance for the loan to be closed (successful). Loan Status (closed loans), on average, is 0.45, which means that loans are fully closed and do not default by 45%. That is a good percentage compared to the average interest rate offered on the platform.

The *Bid-Based-HHI* and *Investor-Based-HHI* are loan concentration measurements. Both measurements are based on the Herfindahl-Hirschman index and are normalized to be between zero and one. On average, both measurements record a value of 0.28, and 0.27 respectively. These percentages show that loans on Renrendai.com are not highly concentrated in general. However, the total number of unique investors that bid on loans is approximately 67 individuals, with a deviation of 107, meaning that certain loans have a higher number of unique investors. This can mean at certain points, there are a lot of funders for a specific loan, whereas for other loans a small number of lenders account for the entire loan fund. Loans have a maturity of approximately 24 months, meaning that most listings on the platform are considered long-term investments with a maturity of 24 months. Borrowers have a debt-to-income ratio (DTI) of 33% on average. Although borrowers on this platform might have a high debt-to-income ratio, they still have 0 outstanding debt in their balance. Therefore, loans associated with 0 outstanding debt are more likely to get funded because investors will be confident in investing in that loan. Finally, 29% of the loans are fully funded by human investors.

Table 3.2: Descriptive statistics: pre-regulation vs post-regulation

	(1)	(2)	(3)	(4)	(5)
	Mean	Std	Mean	Std	Diff
	Pre 2017 Regulation		**Post 2017 Regulation**		**Difference: Pre vs Post**
Interest Rate	0.102	0.008	0.098	0.004	0.004***

Risk-Adjusted Interest Rate	0.155	0.012	0.149	0.006	0.006***
Inflation Rate	0.019	0.002	0.017	0.002	0.001***
Bid-Based-HHI	0.499	0.314	0.183	0.235	0.316***
Investor-Based-HHI	0.488	0.300	0.179	0.233	0.309***
Unique Number of Lenders	125.00	142.70	58.46	88.64	66.53***
Total Number of Bids	125.96	144.66	58.752	89.26	67.21***
Maturity	32.927	8.614	34.418	5.584	-1.491***
Loan Size	84,877	49,139	69,851	33,094	15,025***
Debt-to-Income Ratio	0.631	1.770	0.216	0.308	0.415***
Loan Status (1 = Closed)	0.399	0.490	0.136	0.343	0.263***
Funding Type (1 = Manual)	0.043	0.202	0.047	0.211	-0.004***

Notes: This table represents the t-test for the mean difference between pre the 2017 financial regulation and post the 2017 financial regulation. Interest Rate is the interest rate of the loan. Risk-Adjusted Interest Rate is the interest rate that is adjusted by the risk of the loan. Bid-Based-HHI is a bid-number-based Herfindahl index (0,1] that shows the concentration of the loan. Investor-Based-HHI is a investor-based Herfindahl index (0,1] that shows the concentration of the loan. Total Number of Bids is the total number of bids attempted on loan. Maturity is the duration of the loan. Loan Size is the amount requested to fund a loan. Number of Unique Investors is the number of not repeated investors that are bidding on a loan. Debt-to-Income Ratio is the debt-to-income ratio for borrowers. Loan Status is a dummy variable that is equal to 1 if the loan was fully funded/closed, 0 otherwise. Funding Type is a dummy variable that equals 1 if human investors fully funded the loan, 0 otherwise.

Table 3.2 presents the summary statistics of all variables before and after the period of the 2017 announcement. After the regulation, borrowers' interest rates on the platform decreased, meaning that borrowers started lowering the return offered on listings. In particular, borrowers started to take advantage of the massive flow of money that happened due to the event by lowering interest rates. Inflation rate also decreased after the regulation. The concentration measurements that the *Bid-Based-HHI* denotes, *Investor-Based-HHI,Unique Number of Lenders, and Total Numbe of Bids* decreased after the 2017 financial announcement implying that borrowers started having lower credit risk (e.g., Chandera et al., 2021). Maturity increased after the regulation inferring that borrowers also take longer to repay lenders their money back. Since the regulation obliged individuals to report fees that exceed RMB200,000, the *Loan Size* on Renrendai.com decreased. Additionally, borrowers gained from the regulation by lowering their debt-to-income ratio.

3.6 Methodology

The methodology section introduces the concentration measurements and the econometric specification.

3.6.1 Concentration measurements

Most existing studies rely on several indicators in order to measure the level of concentration (see, e.g., Cen et al., 2018; Huang et al., 2016; Irvine et al., 2016; Itzkowitz, 2013; Patatoukas, 2012). The first indicator used by previous literature is a binary variable where it will equal one if a supplier has one or more than one customer that holds 10% or more of the total sales and zero. The second indicator used is the Herfindahl-Hirschman Index (HHI) of sales to top customers. The third proxy is a ratio of the sum of the total sales to all major customers to the firm's total sales. There has been a positive statistical correlation between the measures mentioned previously (e.g., Dhaliwal et al., 2016). Sufi (2007) and Lin et al. (2012) used four proxy measurements for syndication concentration based on the total number of lenders, the dollar amount, and percentage of the loan kept by the lead arranger Herfindahl index based on lenders' shares. In this study, we are going to use three measurements for loan concentrations. The first variable is the entire number of investors that funded a loan. The second concentration proxy measurement is based on the HHI and is based on the total number of bids attempted on loan[34]. To make it more precise, the bid-based Herfindahl-Hirschman Index is computed at loan level as follows:

$$HHI = \sum_{s \in S_1} (Q_{is}/Q_i)^2 \tag{3.1}$$

Where $Q_{is} = \sum_t q_{ist}$ is the total number of bids on borrower i and loan s and $Q_i = \sum_s Q_{is}$ is the total number of bids attempted by lenders on borrower i. The reason behind measuring HHI based on the number of bids is because bids volume on a loan can provide to which extent lenders are interested in a loan. The more investors bid on a loan, the more likely they are interested in adding this loan to their portfolio. The rationale behind using this HHI indicator is that it shows us in later investigations whether investors started bidding excessively on loans. Also, a concentration indicator can tell if investors held higher shares in the loan which means that they left no competition for others to join and fund a loan. It also shows if the loan, or market, is competitive or not. This uniqueness in these measurements is not provided when using the total number of bids for example. To have extra robustness checks, we include a second proxy for concentration and is the total number of unique investors that is used by existing works (e.g., Lin et al., 2012; Sufi, 2007).

3.6.2 Econometric specification

Before addressing our main research question concerning the impact of the financial announcement of loan concentration, we would like to investigate the influence of this regulation on some loan indicators, which in return will briefly show how individuals on Renrendai.com platform reacted. Our approach looks at borrowers who placed more than one bid during their time on the platform. Therefore, we drop those individuals who listed only one

[34] As Sufi (2007) and Lin et al. (2012) did, we follow their measurement for concentration while making some adjustments for the Herfindahl-Hirschman Index.

loan and end up with a sample of 37,000 borrowers. Next, because our primary interest is documenting the impact of the 2017 financial shock, we focus on and keep only borrowers present before and after the event in the sample to run the regression. This period is relatively short. So, we estimate the predictors at the borrower-loan level. Therefore, our sample size is reduced to approx. 11,000 borrowers. In an Ordinary Least Square (OLS) model, we run the following specification:

$$\text{Loan Indicators}_{\mathrm{i,t}} = \beta_0 + \beta_1 \mathrm{R}(\mathrm{t} \in \text{Regulation})_{\mathrm{i,t}} + \beta_2 \text{Loan}_{\mathrm{i},\gamma} + \beta_3 \text{Inflation}_{\mathrm{i,t}} + \delta_{\mathrm{i}} + \varepsilon_{\mathrm{i,t}} \quad (3.2)$$

Where subscript *i* indicates the borrower and subscript *t* indicates the number of loan listed by the borrower (e.g., 0.1,2,3….N). $\text{Loan Indicators}_{\mathrm{i,t}}$ represents three indicators of a loan: Interest Rate, Risk-Adjusted (RA) Interest Rate, Loan Size, and Loan Maturity. The logarithm of one plus loan maturity (in months) measures the later indicator. Loan Size is the logarithm of one plus the loan amount. Interest Rate is the return that borrowers set for a loan. RA-Interest Rate is the risk-adjusted Interest Rate. RA-Interest Rate is measured using the following formula: $\frac{\textbf{Interest}}{\textbf{Risk}}$ where Interest is the interest rate of the loan and risk is the risk score of the loan. $\mathrm{R}(\mathrm{t} \in \text{Regulation})$ is a binary variable that equals 1 when controlling for all the months after the regulation, 0 otherwise. $\text{Loan}_{\mathrm{i},\gamma}$ is a vector of loan characteristics such as debt-to-income ratio of a borrower, maturity, status, funding type, and the total number of bids on a loan. Debt-to-Income ratio is the debt-to-income ratio. Loan Status is a binary variable that equals to 1 if the loan is fully funded and closed, 0 otherwise. Funding Type is a binary variable that equals to 1 if the loan was funded using only bids that are attempted by human investors, 0 otherwise. Inflation is the inflation rate in China. δ_{i} is borrower fixed effect and the standard errors are clustered at loan level. $\varepsilon_{\mathrm{i,t}}$ is the error term. Overall, we expect a negative correlation between the three loan indicators and the regulation dummy. All variables' definitions are found in Online Appendix of Table TA4.

Because the shock occurred at the end of July, we consider the one-month period covering the regulation as regulation months. Therefore, the control variables of our regression include ten dummies to capture the responses of concentration measures to the regulation that the Chinese government imposes. Each dummy represents one month. Therefore, the model will include monthly regulation indicators for two months before the announcement and eight starting from the announcement month. In an Ordinary Least Square (OLS) model, we run the following specification:

$$\text{Concentration Indicators}_{i,t} = \beta_0 + \sum_{n=1}^{2} \beta_1 \,\text{Shock}(-n)_t + \sum_{n=0}^{8} \beta_2 \,\text{Shock}(+n)_t + \beta_3 \text{Loan}_{i,\gamma} + \beta_4 \text{Inflation}_{i,t} + \delta_i + D_{i,\gamma} + \varepsilon_{i,t} \tag{3.3}$$

Where subscript i indicates the borrower and subscript t indicates the loan listed. $\text{Concentration Indicators}_{i,t}$ consist of two indicators that are HHI that is explained in section 5.1, and the second indicator is measured by the number of unique lenders that invested in a loan. $Shock(-n)_t$ Indicates the months included before the regulation.[35] For example $Shock(-1)_t$ is a binary variable that equals to 1 in the month that it is directly before July 2017, zero otherwise. $Shock(+n)_t$ starts from the month of the regulation (July 2017) and continues for seven months after that. For example, $Shock(+1)_t$ is a binary variable that equals to 1 if it is August 2017, zero otherwise. The remaining variables remain the same as the ones presented in equation (3). δ_i is borrower fixed effect and $D_{i,\gamma}$ is a vector of time fixed effect such day and hour of listing. $\varepsilon_{i,t}$ is the error term.

Next, we know that both loan concentration and interest rates decreased after the regulation. Previous works (e.g., Patatoukas, 2012) claimed that higher concentration is associated with higher profitability. Therefore, we would like to inspect the correlations between some concentration measurements and loan indicators.[36] Also, an interaction term between the financial regulation dummy and interest rates is included in this model. The model now takes the following form:

$$\text{Concentration Indicators}_{i,t} = \beta_0 + \beta_1 \text{R}(t \in \text{Regulation})_{i,t} + \beta_2 \text{Loan}_{i,\gamma} + \beta_3 \text{Inflation}_{i,t} + \beta_4 \text{R}(t \in \text{Regulation}) * \text{Interest Rate}_{i,t} + \delta_i + \varepsilon_{i,t} \tag{3.4}$$

Everything remains the same as the previous models. $\text{R}(t \in \text{Regulation}) * \text{Interest Rate}_{i,t}$ is an interaction term between the after regulation dummy and loan interest rates. We expect to see a positive correlation between the interaction term and concentration indicators.

[35] In further examination, we also include $Shock$ as binary variable that equals to 1 for the entire period after the regulation, zero otherwise. The impact of the shock is similar to when we control for several monthly dummy shocks.

[36] Previous literature has also focused on the factors that affect the structure of loan syndicates. Some studies shed the light on the type of borrower, size, and credit rating on a group of lenders and concentration ratio (Dennis and Mullineaux, 2000; Sufi, 2007). Additionally, other works analyse whether financial hardships (Lee et al., 2010; Lee and Mullineaux, 2004) and the location of a borrowing firm's operations (Ge et al., 2018) affect the structure of loan syndication.

3.7. Empirical analysis

We start our analysis by reporting the impact of the regulation on some loan indicators such as interest rate, loan amount, and loan maturity in table 3.3. Next, we present the impact of the 2017 financial announcement, using monthly shocks indicators on loan concentration. Furthermore, table 3.4 introduces an interaction term between interest rate and the period after the regulation. Then, a placebo test is presented. Finally, table 3.5 reports a robustness check.

3.7.1 Borrower's reaction to the financial regulation

In this section, we investigate the effect of the financial announcement on some loan indicators. This event has changed the way borrowers behave on the platform. Individuals are likely to react to news and change their behaviour in p2p lending markets (see, e.g., Cheng et al., 2020).[37] Therefore, the upcoming table talks about characteristics that the borrower can set and how they change compared to the 2017 financial announcement. Columns 1 and 2 use interest rate and risk-adjusted interest rate, respectively; column 3 uses loan size, and column 4 uses loan maturity as a dependant variable.

Table 3.3: Loan indicators and financial regulation

	(1)	(2)	(3)	(4)
	Interest Rate	**RA-Interest Rate**	**Loan Size**	**Loan Maturity**
After Regulation	-0.407***	-0.616***	-5.760***	3.900***
	(0.000)	(0.000)	(0.009)	(0.004)
Debt-to-Income Ratio	-0.066***	-0.100***	-4.397***	-8.864***
	(0.000)	(0.000)	(0.004)	(0.005)
Loan Status (1 = Closed)	0.427***	0.649***	-43.904***	-17.189***
	(0.000)	(0.000)	(0.014)	(0.008)
Funding Type (1 = Manual)	0.228***	0.345***	-0.734	1.892**
	(0.000)	(0.000)	(0.018)	(0.007)
Log (Total Number of Bids)	-0.060***	-0.091***	15.442***	2.596***
	(0.000)	(0.000)	(0.004)	(0.002)
Inflation Rate	-0.161***	-24.25***	1025.49***	628.08***
	(0.000)	(0.000)	(0.018)	(0.008)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Observations	22,842	22,842	22,842	22,842
R-Squared	0.624	0.625	0.809	0.837

Notes: This table shows the regression results of the impact of the financial regulation on loan indicators. The dependent variables in columns 1,2 3, and 4 are *Interest Rate, Risk-Adjusted Interest Rate, Loan Size, and Loan Maturity,* respectively. Interest Rate is the interest rate of the loan. Risk-Adjusted Interest Rate is the interest rate that is adjusted by the risk of the loan. Loan Size is the loan size and is measured by the logarithm of the loan amount plus 1. Maturity is the loan duration and is measured by the logarithm of maturity plus one. After Regulation is a dummy variable that equals to 1 for the period after the regulation, 0 otherwise. Debt-to-Income

[37] In their paper, they show that the 2015 Ezubao scandal in China resulted in reducing loan amounts and increasing interest rates on Renrendai.com platform.

Ratio is the debt-to-income ratio for borrowers. Loan Status is a dummy variable that equals 1 if the loan was fully funded and closed, 0 otherwise. Funding Type is a dummy variable that equals to 1 if human investors fully funded the loan, 0 otherwise. Log (Total Number of Bids) is the logarithm of the total number of bids on a loan plus 1. Inflation Rate is the inflation rate in China. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at loan level. Coefficients are multiplied by 100 for presentation purposes.

To detect the impact on loan indicators that happened after the regulation, we inspect the coefficient that is associated with *After Regulation* variable. Table 3.3 shows that the 2017 financial regulation had a negative impact on interest rates. In column (1) *After Regulation* has a negative coefficient which means that the 2017 financial announcement decreases the loan interest rates. The results from the estimation show an immediate decrease in interest rates of about 40 basis points (0.407%). This implies that, after the regulation, borrowers set lower returns on loans to take advantage of the regulation. This allowed individuals to borrow more money with lower repayment rates. This result is robust as we use another measurement in column (2) for returns offered by adjusting the interest rates by the riskiness of borrowers. The influence of interest rates on borrowing has been discussed in previous works (e.g., Garín et al., 2019; Jappelli and Pistaferri, 2007; Martins and Villanueva, 2006) concerning different sectors and fields.

As for loan size, the results indicate that the loan amounts that borrowers request has decreased after the regulation. When there is less uncertainty in the market, borrowers attract investors using big loan amounts. In particular, requests for a higher loan amount are riskier to where they increase leverage and default incentives (e.g., Galema, 2020). Therefore, it seems that borrowers are decreasing their loan amounts to make investors feel safe when bidding, considering the high uncertainty that the financial announcement has created. Although the regulation made more funds available in the market, that does not mean that investors will just invest blindly in loans. Individuals still need to feel that borrowers can repay the requested amount in addition to the interest charged.

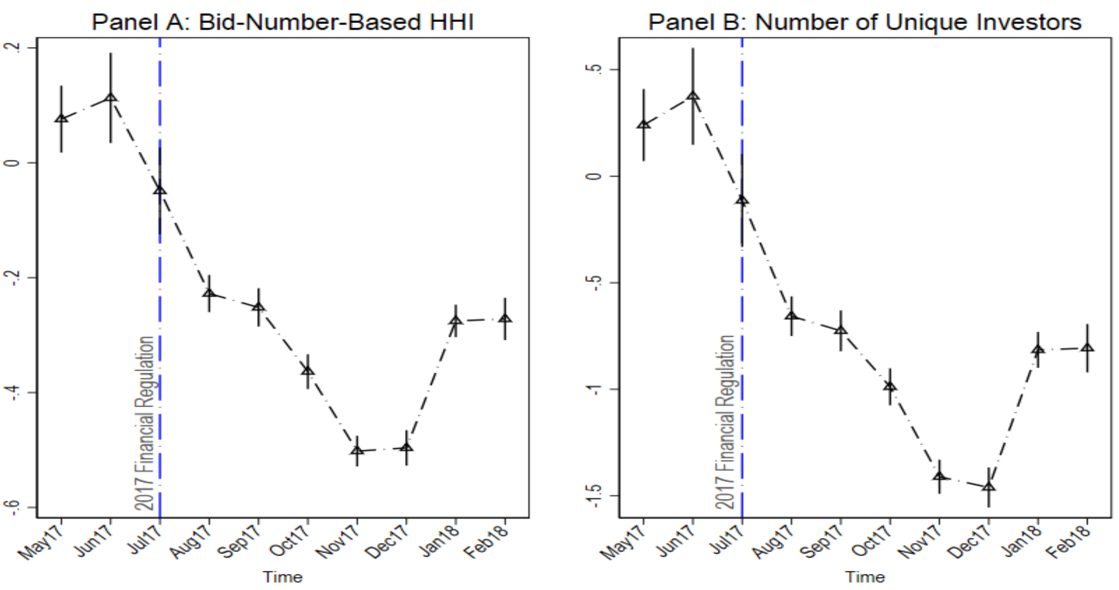
We observe that the maturity of loans increased after the 2017 announcement, inferring that borrowers were assigned a longer duration to repay the loan. This is evident in column 4 by the positive coefficient on *After Regulation*. This can tell us that borrowers are also taking advantage of the situation by increasing the duration to repay loans. In particular, it will further encourage individuals to borrow more money as they will take a longer time repaying the funds, leading to lower monthly repayments. Thus, the longer it takes to repay a loan, the lower the monthly payments will be. Moreover, the impact that the 2017 event let borrowers to reduce the risk of repaying investors since they will have longer time and lower amounts to repay.

Existing studies have further focused on this issue and claimed increased uncertainty might induce debtors to borrow longer terms to reduce refinancing risks (Diamond and He, 2014; Harford et al., 2014; He and Xiong, 2012). As for inflation, our results show that the more the inflation rate increase, the more the interest rates of loans decrease. As the inflation rate increases by 1% in column (1), the interest rate is subject to decrease by 0.16%.

3.7.2 Investors reaction to the shock

Our analysis is further extended by investigating the impact of the 2017 financial regulation on the concentration of loans. We drop borrowers who were not active on the market during the pre-and post-period of the regulation. Figure 3.3 displays the effects of equation 3.3.

Figure 3.3: Coefficients Plot



Note: This figure shows the coefficients plot for the regulation (months) on concentration indicators that are Bid-Number-Based HHI, and Number of Unique Investors. The blue dashed vertical line marks the month of the financial regulation.

Figure 3.3 investigates the impact of the 2017 financial announcement on loan concentration indicators presented in equation (3.3). The coefficients of month dummy variables indicate that the financial announcement creates an unappealing situation for individual investors. In particular, investors seem to be patient and do not rush to bid on loans that appear on the market after the 2017 event. Panel A shows the impact of the announcement on the bid-number-based Herfindahl index. At the month of the shock, the results seem to be insignificant, indicating that investors did not react instantly at the month of the announcement. However, after one month of announcing the restriction on overseas transactions and transfers, the results show that the *Bid-Number-Based HHI* decreased instantly. This infers that investor are less interested in investing in some loans. [38] Thus, individuals do not rush anymore to invest in opportunities, which might come to several factors such as lowering interest rates. Borrowers, after the regulation, found it cheaper to borrow, which in return led investors to be disinterested. According to existing works (e.g., Zhao et al., 2020), investors are likely to bid less and spend less money when investing in loans with lower interest rates. Panel B considers another concentration indicator: the number of unique investors that funded a listing. Subsequently, the number of lenders that bid on the same P2P loan decreased after one month of the announcement. The results in the Online Appendix of Table TA3.6 show that after one month of the financial regulation, the number of unique investors dropped by 0.28 percentage points. Again, the economic impact is quite significant compared to the previous phase before the event. This further shows that investors are less interested in the loans that are listed on the platform. Regulators thought that this might urge individuals to invest in China more. However, this does not seem the case when it comes to *Renrendai.com* platform.

3.7.3 Loan concentration and profitability

The previous model, presented in section 6.2, does not control for the effects of interest rates after the regulation on the concentration indicators. Therefore, we extend our model by adding an interaction term between financial regulations and interest rates in columns 3 and 4.

Table 3.4: Impact of the regulation on loan concentration

	(1)	(2)	(3)	(4)
	HHI	**Lenders**	**HHI**	**Lenders**
After Regulation	-0.353***	-1.023***	-0.699***	-1.645***
	(0.006)	(0.019)	(0.135)	(0.389)
Interest Rate	-9.282***	-27.195***	-9.834***	-28.186***
	(0.567)	(1.620)	(0.611)	(1.732)
Log (Maturity)	-0.043**	-0.163***	-0.040**	-0.158***
	(0.020)	(0.058)	(0.020)	(0.058)
Log (Loan Size)	0.307***	0.963***	0.308***	0.965***
	(0.008)	(0.024)	(0.008)	(0.024)
Debt-to-Income Ratio	0.013***	0.038***	0.011***	0.034***
	(0.003)	(0.009)	(0.003)	(0.009)
Loan Status (1 = Closed)	-0.032***	-0.070**	-0.030***	-0.067**
	(0.011)	(0.032)	(0.011)	(0.033)
Funding Type (1 = Manual)	-0.102***	-0.292***	-0.100***	-0.289***
	(0.014)	(0.040)	(0.014)	(0.040)

[38] See also Online Appendix of Table TA1 where we present the regression coefficients. The table shows us that after 1 month of the regulation, there was a major impact on the concentration of loans.

Inflation Rate	-16.93***	-56.96***	-16.84***	-56.81***
	(1.327)	(4.041)	(1.329)	(4.047)
Regulation * Interest			3.497**	6.282*
			(1.358)	(3.924)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Observations	22,842	22,842	22,842	22,842
R-Squared	0.438	0.684	0.439	0.684

Notes: This table shows the regression results of the impact of the financial regulation on loan indicators. The dependent variables are the HHI and the number of unique lenders. After Regulation is a dummy variable that equals to 1 for the period after the regulation, 0 otherwise. Interest Rate is the interest rate of the loan. Regulation * Interest is the interaction term between the dummy variable indicating the phase after regulation and between the interest rate of loans. Log (Maturity) is the loan duration and is measured by the logarithm of maturity plus one. Log (Loan Size) is the loan size and is measured by the logarithm of the loan amount plus 1. Debt-to-Income Ratio is the debt-to-income ratio for borrowers. Loan Status is a dummy variable that equals 1 if the loan was fully funded and closed, 0 otherwise. Funding Type is a dummy variable that equals to 1 if human investors fully funded the loan, 0 otherwise. Inflation Rate is the inflation rate in China. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at loan level. Coefficients are multiplied by 100 for presentation purposes.

This table uses After Regulation binary variable as the independent variable rather than the shock months presented in Figure 3.3. Starting with the impact of the financial shock, we find consistent results with Figure 3.3 where the financial regulation had a negative impact on the concentration of loans. This is shown in both columns 1 and 2. Interestingly, the results of this table show a negative correlation between interest rates and loan concentration. According to existing works (e.g., Huang et al., 2021), higher interest rates attract lenders and increase the probability of funding success. Patatoukas (2012) and Cen et al. (2016) showed that higher customer concentration is related to having higher profitability. Mainly, Patatoukas (2012) results indicated that concentration increased performance by 2.20 percent regarding return on assets and 4.71 percent in terms of return on equity.[39] However, the way investors perform in Chinese P2P lending platforms seems to be different. In particular, investors on Renrendai.com seem to be not easily attracted by the high interest that is set on loans. Instead, they prefer to concentrate their attention on loans with lower returns since they are considered safer loans with lower probability of default (see, e.g., He et al., 2021). This result is inconsistent in columns 1 and 2 and is shown by the negative sign that is reported on *Interest Rate*. In column 1, the economic interpretation with be as follows. 1% increase in interest rates will decrease the bid-based HHI by 0.092 in the index of HHI.

When introducing the interaction term in columns 3 and 4, the coefficients of our explanatory variables remain unchanged. Regulation * Interest term is positively and statistically significant

[39] See, e.g., Online Appendix Table A2, we get consistent results when considering the entire sample size. Our result shows that high profitability is associated with higher concentration. But, since we are interested in borrowers that stayed during the pre-and-post regulation period, our results show how it affected them differently later on.

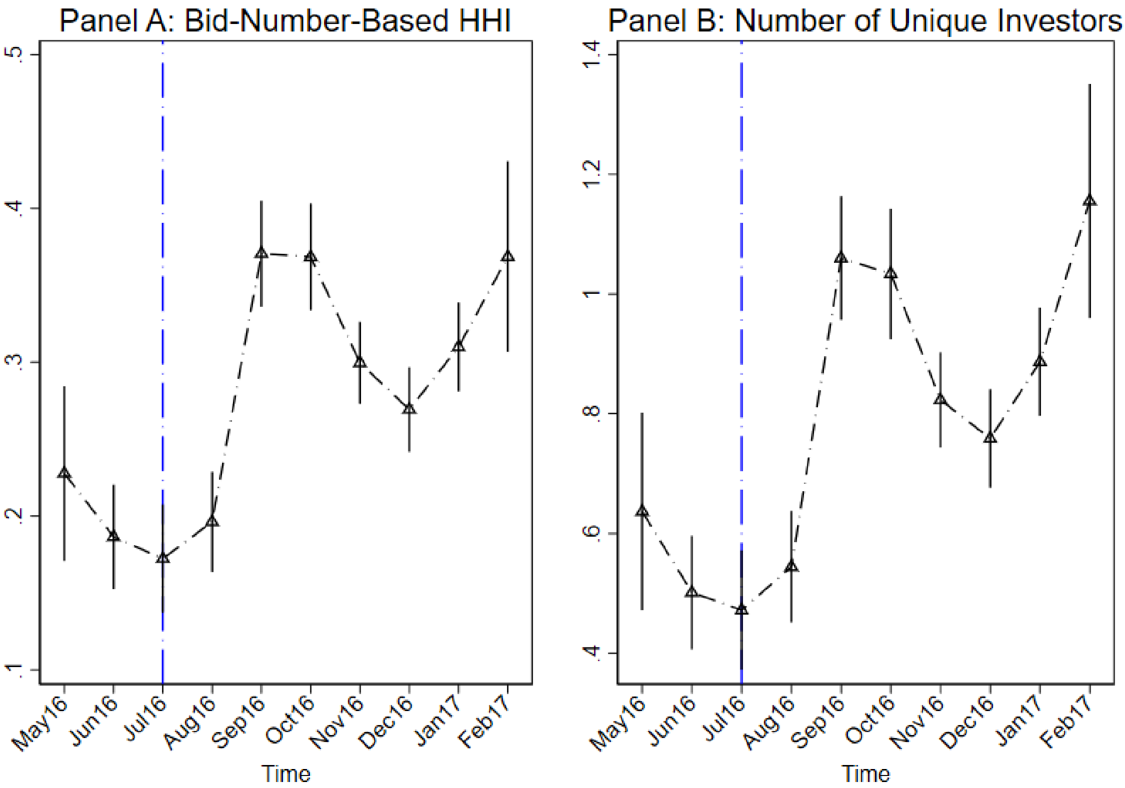
at 1% level in column 3. This suggests a strong relationship between the post-regulation period and loan returns on the concentration of loans. Particularly, after the financial regulation, loans with higher profitability had higher concentration levels from investors, meaning that individual lenders increased their perception of risk in P2P transactions, causing them to demand higher interest rates. Maybe, since they have overseas restrictions, lenders want to get the best possible outcome on their investments in China after the regulation. This result is weaker in column 4 when we consider the number of unique lenders as a concentration indicator. The coefficient is now significant at the 10% level.

Furthermore, log (Maturity) records negative coefficients, suggesting that loans with higher concentration are associated with short-term loans. This result is statistically significant in the three models that are presented in Table 3.4. In economic terms, the interpretation would be that a decrease in Log (Maturity) increases the concentration of a loan by 0.043 percentage points. Thus, one might argue that investors prefer short-term investments to get repaid in a shorter duration. Regarding loan size, our results show that loans with the higher amount needed to be funded are likely to have a higher concentration. Previous works have found a relationship between size and concertation. For example, De Haan and Poghosyan (2012) showed that the negative impact of bank size on bank earnings volatility decreases with market concentration. In a more recent study, Diallo (2017) controlled for bank size and found that the coefficients of interest, namely bank concentration, interacted with financial dependence and the triple interaction term, enter negatively and positively, and statistically significantly different from zero at the 1%, respectively. Our results show that both loan concentration and size are positively correlated with each other, as shown on the coefficient of *Log (Loan Size)*. For loan outcomes, such as the type of funding the loan received, our results show that higher concentrated loans are negatively correlated with *Funding Type* in the four columns. In particular, the estimates suggest that lower manual bidders of loans attract higher concentrations. This result means that other funding types, such as hybrid and automated methods, attract higher loan concentrations. Finally, and consistent with interest rates, the inflation rate plays a role in decreasing the concentration of loans. This means that inflation also makes investors feel disinterested in investing as the rates increase.

3.7.4. Placebo test

In the primary estimations presented in equation 3.3, we observe the reaction of individuals towards the 2017 financial regulation. In this section, we perform a "placebo" test to check whether the changes in the concentration of loans were due to the regulatory shock or seasonal effects. Therefore, we re-estimate model 3.3 using the sample that takes the monthly shocks, dummies, from May 2016 to February 2017. This period is exactly one year before the original shock months that we estimate in model 3.3.

Figure 3.4: Coefficients plot for placebo test



Note: This figure shows the placebo coefficients plot for the 2016 (months) on concentration indicators that are Bid-Number-Based HHI, and Number of Unique Investors. The blue dashed vertical line marks the month of the made-up 2016 regulation.

The aim of the placebo test is to investigate the behaviour of investors in a similar period time in which the regulation did not happen. Then, we compare the results of this new period tested with the old one in which the regulation existed. We mainly run the three regressions above with their corresponding sample for the same 10-month sample period while considering 2016 as the central part of the analysis. The results are reported in Figure 3.4 and Online Appendix Table TA3-9. We find that Bid-Based HHI increased during that period. Additionally, the same thing applies to the number of unique lenders that invested in a loan. We find that the concentration of loans increased gradually during that time. These estimates suggest that the economic significance of the monthly dummy variables that are controlled for in model 2 are not driven by some seasonal effects. Therefore, this further supports our results by showing that the massive changes in individuals' behaviour are due to the 2017 financial regulation.

3.7.5 Robustness check

In what follows, we run the same model presented in Eq (3.4) using different proxy loan concentration indicators. The first measurement is calculated in the same way as the HHI measurement in section 5.1. The difference in the new variable is that it is based on the number of investors instead of the bid number. The second concentration indicator is measured using the total number of bids attempted on a loan. Therefore, columns 1 and 3 use the investor based HHI and columns 2 and 4 use the number of bids.

Table 3.5: Robustness check (HHI Proxy)

	(1)	(2)	(3)	(4)
	Investor Based HHI	**Number of Bids**	**Investor Based HHI**	**Number of Bids**
After Regulation	-0.352***	-1.026***	-0.711***	-1.603***
	(0.006)	(0.019)	(0.135)	(0.389)
Interest Rate	-9.290***	-27.178***	-9.862***	-28.097***
	(0.566)	(1.622)	(0.610)	(1.733)
Log (Maturity)	-0.044**	-0.161***	-0.041**	-0.156***
	(0.020)	(0.058)	(0.020)	(0.058)
Log (Loan Size)	0.307***	0.963***	0.309***	0.965***
	(0.008)	(0.024)	(0.008)	(0.024)
Debt-to-Income Ratio	0.013***	0.038***	0.011***	0.034***
	(0.003)	(0.009)	(0.003)	(0.009)
Loan Status (1 = Closed)	-0.032***	-0.068**	-0.030***	-0.066**
	(0.011)	(0.033)	(0.011)	(0.033)
Funding Type (1 = Manual)	-0.116***	-0.248***	-0.114***	-0.245***
	(0.014)	(0.040)	(0.014)	(0.040)
Inflation Rate	-16.99***	-56.80***	-16.90***	-56.67***
	(1.326)	(4.047)	(1.328)	(4.053)
Regulation * Interest			3.625***	5.826*
			(1.357)	(3.926)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Observations	22,842	22,842	22,842	22,842
R-Squared	0.446	0.689	0.446	0.689

Notes: This table shows the regression results of the impact of the financial regulation on loan indicators. The dependent variables are the Investor Based HHI and the total number of bids on a loan. After Regulation is a dummy variable that equals to 1 for the period after the regulation, 0 otherwise. Interest Rate is the interest rate of the loan. Regulation * Interest is the interaction term between the dummy variable indicating the phase after regulation and between the interest rate of loans. Log (Maturity) is the loan duration and is measured by the logarithm of maturity plus one. Log (Loan Size) is the loan size and is measured by the logarithm of the loan amount plus 1. Debt-to-Income Ratio is the debt-to-income ratio for borrowers. Loan Status is a dummy variable that equals 1 if the loan was fully funded and closed, 0 otherwise. Funding Type is a dummy variable that equals to 1 if human investors fully funded the loan, 0 otherwise. Inflation is the inflation rate in China. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at loan level. Coefficients are multiplied by 100 for presentation purposes.

When inspecting the coefficients of the robustness check, we find consistent results with those that are presented in table 4 when measuring HHI using the number of unique investors. The number of bids on a loan and the number of unique investors involved in a loan is similar to some extent. This can explain the similarity in the result. The estimates suggest that after the regulation, investors were less involved in loans. This disinterest can have many reasons such as borrowers taking advantage of the situation by decreasing the return on investments. Additionally, the results again show that profitability and concentration are negatively correlated, meaning that investors prefer to be involved in lower profitable investments on Renrendai.com. This is explained by the fact that low-return loans have a lower rate of default. However, after the regulation, lenders start to associate themselves with listings that have higher returns. The reason behind that is that maybe individuals want to make the best out of their money by generating higher profits during uncertain times. In columns 2 and 4, when we measure concentration using the total number of bids attempted on a loan, we also find consistent results with those reported in previous tables.

3.8. Conclusion

We study the response of borrowers and investor's behaviour to a well-identified financial regulation. The 2017 Chinese financial announcement represented a quasi-natural experiment that forced individuals to spend more money in China and set restrictions on those who invest or transfer money overseas. This regulation increased the money in the hands of Chinese investors. As a result, lenders had more money to spend in China, leading borrowers to change their behaviour when listing a loan on P2P lending platforms.

This paper employs an extensive and comprehensive dataset of loan listings in the Chinese P2P lending market. This dataset allows us to capture the reaction of borrowers toward the impact of a financial shock and provides valuable insight into how investors responded in return. We observe that the loans of Chinese borrowers were instantly affected by the available funding, causing a significant drop in loans' interest rates. Consequently, the activity on Renrendai.com platform became inefficient as investors felt that they were less interested in bidding on loans. Instead, individual investors were only interested in high-profitable loans after the regulations. This can be explained by the fact that borrowers took advantage of this announcement by loan size and increased repayment duration.

Online Appendix A

Table TA3.6: Concentration and regulation (monthly regulations dummies)

	(1)	(2)	(3)	(4)
	HHI	**Lenders**	**HHI**	**Lenders**
Regulation $_{\mathrm{N-2}}$	0.061**	0.191**	0.076**	0.240***
	(0.029)	(0.085)	(0.030)	(0.086)
Regulation$_{\mathrm{N-1}}$	0.081**	0.285**	0.113***	0.375***
	(0.039)	(0.113)	(0.040)	(0.116)
Regulation$_{\mathrm{N+0}}$	-0.092**	-0.227**	-0.049	-0.114
	(0.037)	(0.108)	(0.039)	(0.111)
Regulation$_{\mathrm{N+1}}$	-0.228***	-0.671***	-0.228***	-0.657***
	(0.016)	(0.045)	(0.017)	(0.047)
Regulation$_{\mathrm{N+2}}$	-0.258***	-0.755***	-0.252***	-0.726***
	(0.016)	(0.046)	(0.017)	(0.049)
Regulation$_{\mathrm{N+3}}$	-0.381***	-1.052***	-0.363***	-0.989***
	(0.015)	(0.042)	(0.015)	(0.044)
Regulation$_{\mathrm{N+4}}$	-0.499***	-1.407***	-0.502***	-1.411***
	(0.012)	(0.036)	(0.014)	(0.041)
Regulation$_{\mathrm{N+5}}$	-0.498***	-1.468***	-0.496***	-1.461***
	(0.015)	(0.045)	(0.016)	(0.048)
Regulation$_{\mathrm{N+6}}$	-0.265***	-0.791***	-0.275***	-0.815***
	(0.014)	(0.041)	(0.014)	(0.043)
Regulation$_{\mathrm{N+7}}$	-0.296***	-0.876***	-0.272***	-0.807***
	(0.018)	(0.056)	(0.019)	(0.058)
Interest Rate	-7.703***	-22.626***	-7.113***	-20.685***
	(0.591)	(1.692)	(0.604)	(1.736)
Log (Maturity)	-0.051**	-0.186***	-0.057***	-0.207***
	(0.020)	(0.058)	(0.020)	(0.059)
Log (Loan Size)	0.331***	1.033***	0.325***	1.018***
	(0.008)	(0.024)	(0.008)	(0.024)
Debt-to-Income Ratio	0.012***	0.034***	0.011***	0.032***
	(0.003)	(0.009)	(0.003)	(0.009)
Loan Status (1 = Closed)	0.008	0.045	0.006	0.037
	(0.011)	(0.032)	(0.011)	(0.032)
Funding Type (1 = Manual)	-0.107***	-0.311***	-0.056***	-0.161***
	(0.014)	(0.040)	(0.016)	(0.046)
Inflation Rate	-3237.010***	-9880.795***	-2777.448***	-8629.212***
	(216.445)	(650.015)	(223.501)	(668.848)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Day of Listing Fixed Effect	No	No	Yes	Yes
Hour of Listing Fixed Effect	No	No	Yes	Yes
Observations	22,842	22,842	22,842	22,842
R2	0.428	0.678	0.444	0.687

Notes: This table shows the impact of financial regulation on loan concentration. The dependent variables are the HHI and the number of unique lenders. Regulation$_{N-k,(k-1)}$ are dummy variables that show whether the month is (k) or (k-1) months before the month of the regulation. For example, RegulationT-1 equals 1 if the month is one month before the regulation, otherwise it is 0. Regulation are dummy variables that show whether the month is (k) or (k+1) months following the month of the regulation. Remaining variables remain the same as in previous tables. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at loan level.

Table TA3.7: Performance and concentration

	(1)	(2)
	HHI	**Lenders**
Interest Rate	0.592***	1.340***
	(0.096)	(0.323)
Log (Maturity)	-0.075***	-0.237***
	(0.005)	(0.016)
Log (Loan Size)	0.264***	0.897***
	(0.004)	(0.011)
Debt-to-Income Ratio	0.033***	0.100***
	(0.003)	(0.009)
Loan Status (1 = Closed)	-0.070***	-0.125***
	(0.005)	(0.014)
Funding Type (1 = Manual)	-0.182***	-0.611***
	(0.007)	(0.018)
Borrower Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Observations	82,868	82,868
R-Squared	0.349	0.748

Notes: This table shows the correlations between loan concentration and other characteristics. The dependent is HHI and number of unique lenders. Interest Rate is the interest rate of the loan. Risk-Adjusted Interest Rate is the interest rate that is adjusted by the risk of the loan. Log (Maturity) is the loan duration and is measured by the logarithm of maturity plus one. Log (Loan Size) is the logarithm of loan amount requested to fund a loan plus one. Debt-to-Income Ratio is the debt-to-income ratio for borrowers. Loan Status is a dummy variable that is equal to 1 if the loan was fully funded and closed, 0 otherwise. Funding Type is a dummy variable that equals to 1 if human investors fully funded the loan, 0 otherwise. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at loan level.

Table TA3.8: Concentration and regulation (placebo monthly regulations dummies)

	(1)	(2)
	HHI	**Lenders**
Regulation $_{\mathrm{N-2}}$	0.283***	0.827***
	(0.030)	(0.086)
$\mathrm{Regulation}_{\mathrm{N-1}}$	0.241***	0.688***
	(0.018)	(0.052)
$\mathrm{Regulation}_{\mathrm{N+0}}$	0.226***	0.658***
	(0.019)	(0.054)
$\mathrm{Regulation}_{\mathrm{N+1}}$	0.253***	0.738***
	(0.018)	(0.050)
$\mathrm{Regulation}_{\mathrm{N+2}}$	0.430***	1.264***
	(0.019)	(0.056)
$\mathrm{Regulation}_{\mathrm{N+3}}$	0.435***	1.261***
	(0.019)	(0.059)
$\mathrm{Regulation}_{\mathrm{N+4}}$	0.353***	1.007***
	(0.015)	(0.044)
$\mathrm{Regulation}_{\mathrm{N+5}}$	0.300***	0.864***
	(0.015)	(0.043)
$\mathrm{Regulation}_{\mathrm{N+6}}$	0.265***	0.731***
	(0.015)	(0.048)
$\mathrm{Regulation}_{\mathrm{N+7}}$	0.325***	1.006***
	(0.031)	(0.099)
Interest Rate	2.123***	5.991***
	(0.579)	(1.644)
Log (Maturity)	-0.221***	-0.681***
	(0.020)	(0.059)
Log (Loan Size)	0.322***	1.010***
	(0.008)	(0.025)
Debt-to-Income Ratio	0.021***	0.061***
	(0.003)	(0.010)
Loan Status (1 = Closed)	0.053***	0.177***
	(0.011)	(0.033)
Funding Type (1 = Manual)	-0.084***	-0.238***
	(0.016)	(0.045)
Inflation Rate	-18.079***	-62.022***
	(1.905)	(5.700)
Borrower Fixed Effect	Yes	Yes
Day of Listing Fixed Effect	Yes	Yes
Hour of Listing Fixed Effect	Yes	Yes
Observations	22,838	22,838
R2	0.430	0.680

Notes: This table shows the impact of financial regulation on loan concentration. The dependent variables are the HHI and the number of unique lenders. $\mathrm{Regulation}_{N-k,(k-1)}$ are dummy variables that show whether the month is (k) or (k-1) months before the month of the regulation. For example, RegulationT-1 equals 1 if the month is one month before the regulation, otherwise it is 0. $\mathrm{Regulation}_{N+k,(k+1)}$ are dummy variables that show whether the month is (k) or (k+1) months following the month of the regulation. Remaining variables remain the same as in previous tables. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Standard errors are clustered at loan level.

Table TA3.9: Variable's Definition

Variable	Description
After Regulation	Is a dummy variable that equals 1 for the period after July 2017, 0 otherwise.
Interest Rate	The interest rate of the loan.
Risk-Adjusted Interest Rate	Is the interest rate that is adjusted by the risk of the loan (Interest / Risk).
Bid-Based-HHI	Is a bid-number-based Herfindahl index (0,1] that shows the concentration of the loan.
Investor-Based-HHI	Is an investor based Herfindahl index (0,1] that shows the concentration of the loan.
Maturity	Maturity is the duration (in months) of the loan.
Loan Size	The amount requested to fund a loan.
Number of Unique Investors	The number of not repeated investors that are bidding on a loan.
Number of Bids on Loan	The total number of bids placed on a loan.
Debt-to-Income Ratio	The debt-to-income ratio for borrowers.
Loan Close (1=Yes)	A dummy variable that equals to 1 if the loan was fully funded, 0 otherwise.
Manual Funding (1=Yes)	A dummy variable that equals to 1 if human investors fully funded the loan, 0 otherwise.
Inflation Rate	Is the inflation rate in China.

Notes: This table displays the definition of the variable.

Chapter 4. Investor Expertise and Suboptimal Financial Decisions.[40]

[40] In this chapter, we use material that is submitted to University of Birmingham for the assignment of Advanced Research Methods module and for the Annual Review.

4.1. Introduction

Being experienced can be decisive when it comes to making decisions.[41] For example, gaining experience can improve individuals' investment performance by adjusting their behaviour over time (e.g., Bellofatto et al., 2018; Boolell-Gunesh et al., 2012). However, most of them fail to keep up with this expectation. While there are reasons behind this underperformance, one of the most significant reasons cited is investor psychology (e.g., Han and Kumar, 2013; Kumar, 2009). Investors throughout history have been known to display behaviour biases that lead them to investment mistakes (Merkle, 2017). These mistakes can sometimes be costly and result in huge losses (e.g., Barber et al., 2009). This paper investigates how experienced investors commit financial mistakes in microlending markets.

The success of mature individuals when it comes to investment-related decisions is associated with learning from their mistakes and overcoming their emotions. Although experienced investors are less prone to behavioural biases (Feng and Seasholes, 2005), investment experience can still affect individuals in anchoring bias and overconfidence (Chen et al., 2007; Mak and Ip, 2017). Overconfidence can interfere in investors' line of judgment and end them with financial mistakes (e.g., Barber and Odean, 2001; Camerer and Lovallo, 1999; Dorn and Huberman, 2005; Merkle, 2017; Odean, 1998, 1999; Statman et al., 2006). Also, social Scientists believe that individuals, in general, are rational in their way of thinking (Kahneman, 2011). However, consistent rationality can be doubtful where other factors can interfere with people’s sense of rationality (e.g., Druckman and McDermott, 2008; Loewenstein et al., 2001).

To conduct this study, we collect our data from Renrendai.com, which is considered one of China's leading P2P lending platforms. The data span from October 2010 to October 2018 and has detailed information about the biddings placed on loans. The collection of the data resulted in more than 70 million observations at the investor-bid level. This data has several unique aspects compared to a traditional financial market. FinTech in general and P2P lending platforms in specific promote fast lending decisions, easy entry and exit requirements, and lower transaction costs and information costs. These characteristics make the peer-to-peer lending market a well-suited environment to study the behaviour of lenders. It also opens more accessible opportunities for new investors.

[41] See “Success with money is in the mind (Financial Times, October 02, 2019) (Available at: https://www.ft.com/content/1edb2662-12a6-11e6-91da-096d89bd2173) , accessed on May 15, 2020.

With the emergence of peer-to-peer (P2P) lending in China, investors now have more opportunities to invest in financial projects. However, some individuals seem to commit the same mistakes that they attempt in traditional financial markets. Our study provides evidence that experienced investors in online lending markets fall into attempting costly decisions. Particularly, experienced investors are more likely to commit suboptimal decisions due to showcasing overconfidence behaviour. However, naïve individuals are likely to be more cautious by falling less into making unacceptable financial decisions. In particular, as investors become experienced, they do not seem to learn from their wasteful historical decisions and keep making more wrong financial decisions. Finally, experienced individuals are likely to make less profitable decisions.

This paper relates to three strands of literature in finance and economics. First, this study is related to the literature of behavioural determinants of investor's decision-making. Previous works have often shed light on overconfidence (e.g., Barber and Odean, 2000; Deaves et al., 2009, 2010; Glaser and Weber, 2007; Grinblatt and Keloharju, 2009; Merkle, 2017), optimism (e.g., Lobe and Rieks, 2011), overreaction (e.g., Farag, 2014), herding behaviour (e.g., Jiang and Verardo, 2018; Zhang and Liu, 2012), and expert imitation (e.g., Gao et al., 2020). These studies focus on the irrational behaviours of investors in traditional markets and P2P online lending markets. Our paper this strand of literature by showing that overconfidence interferes in investor's line of judgment.

Second, we contribute to the literature of learning from experience. While existing works (e.g., Barber et al., 2020; Linnainmaa, 2011; Mahani and Bernhardt, 2007; Seru et al., 2010) do not abandon the idea of the impact of behavioural motives, they claim that learning alone can be a significant factor in explaining the speculative trading that investors attempt. Our paper relates to this literature by showing that experienced investors do not learn from their mistakes.

Third, this paper relates to the literature on over-investing. Several theoretical models (e.g., Caballé and Sákovics, 2003; K. Daniel et al., 1998; K. D. Daniel et al., 2001; Gervais and Odean, 2001; Kyle and Wang, 1997; Odean, 1998) link active investing with overconfidence that in return affects investors by attempting sub-optimal financial decisions. Our paper complements this strand by showing that more bidding increases overconfidence, leading to increased investing mistakes.

The remainder of the paper is organized as follows. Section 4.2 talks about P2P and Renrendai, Section 4.3 provides the data used in this paper associated with descriptive statistics. Section

4.4 presents the methodology and the econometric specification. Section 4.5 presents our empirical findings. Finally, Section 4.6 concludes the paper.

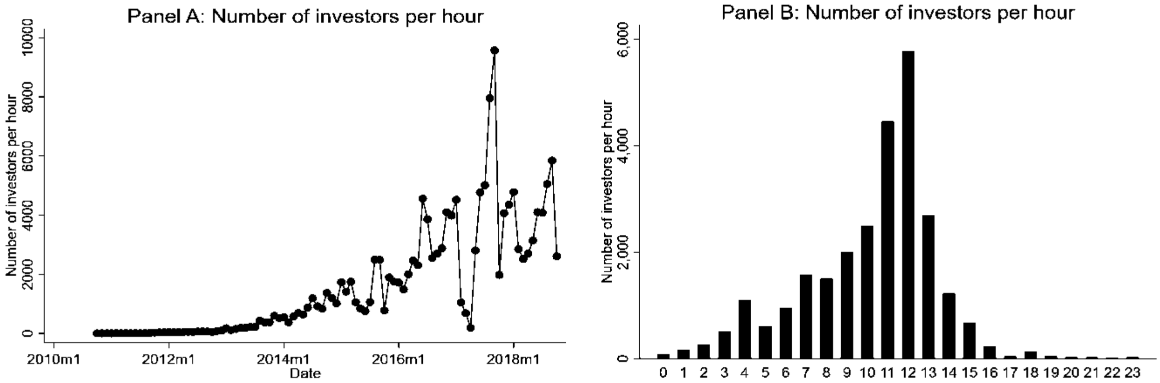
4.2. P2P and Renrendai.com

A new way of investing, called P2P lending, has emerged in China. This tool had a significant impact on the Chinese financial markets, where it caused a sizeable economic boom. Peer-To-Peer lending has proliferated between 2011 and 2015 in China, resulting in 3,500 lending platforms and a loan's total of 980 billion yuan. Peer-to-peer lending is the process through which a lender funds a borrower's loan after matching with each other on the platform. Zopa, United Kingdom-based, is a very well-known P2P lending platform that goes back to February 2005 and is considered an opportunity to cause a boom in the global financial lending markets. China followed later to keep on track with the financial trend and introduced its first P2P lending platform, PPDAI.com, in August 2007. This platform was then followed by Renrendai.com and is labelled as one of China's leading platforms. Since then, the P2P lending markets have promptly developed with more than 2,000 P2P lending platforms by the end of 2016. The P2P market's share surpassed 91 billion dollars of the total outstanding loans in 2016. Individuals or companies with limited or no access to bank loans and investors who invested in these platforms are the reason behind this global online phenomenon's growth. Despite introducing a new law that reduced the annual returns from 20 percent to almost percent, investors did not stop funding loans and investing in the P2P platform.

For bidders, the process to register with the platform is more accessible than for borrowers. Bidders or investors need to register with the forum and have their verification process completed. After they get verified, they start to search for suitable loans and to fund them. Lenders can either fully fund or partially fund a loan where the later decision is considered less risky for investors. Not all listings will become loans on Renrendai.com. Investors at certain times will contribute to a loan and end up incurring the time and transactional costs due to the failure of funding that loan.

The only drawback that investors can be affected by is the high-interest rate set by Renrendai.com, which varies between 13 to 20 percent. Although lenders were affected by this high-interest rate, this has not stopped them from being appealed by the Renrendai.com platform. Therefore, Figure 4.1 will show the number of investors per hour registered with Renrendai.com between 2010 and 2018. Panel A and B show the growth in the number of investors despite the high interest that Renrendai.com set.

Figure 4.1: Number of new investors per hour



Notes: Panel A of this figure shows the number of investors per hour over the period of 2010 and 2018. Panel B shows the number of investors on an hourly basis (from 0 o'clock till 23 o'clock).

4.3. Data

Our large dataset of loan listings and investor biddings was collected from Renrendai.com peer-to-peer lending platform throughout October 2010 and October 2018. The listings dataset has information on the requested amount, listing time, listing date, maturity date, interest rate, and risk level. Investor's dataset has information on each investor's ID, time of their bid, date of their bid, and how much money they spent on funding loans. Based on this information, we can create how much percentage is needed for the loan to be fully funded and how much money investors spend on each funding loan. Borrower's dataset has information on characteristics, such as credit information and personal information like educational level and many more. If a Loan was fully funded and recorded as successful on the platform, we obtain the loan origination date to create how many successful bids each investor has.

Table 4.1: Descriptive statistics, whole sample

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Obs.	Mean	Std	P25	P50	P75
Suboptimal	74,428,003	0.66	0.47	0.00	1.00	1.00
Suboptimal_2	74,428,003	0.70	0.46	0.00	1.00	1.00
Bid Number	74,428,003	386.62	736.72	36.00	134.00	421.00
Active Time	74,428,003	122.86	157.51	12.00	61.00	176.00
Overall Time	74,428,003	457.79	434.32	110.00	338.00	694.00
Closed Bids	74,428,003	207.36	436.23	11.00	61.00	217.00
Bidders	74,428,003	129.05	159.20	25.00	70.00	172.00
DTI Ratio	73,354,874	0.32	0.77	0.11	0.22	0.38
Gender	74,428,003	0.63	0.48	0.00	1.00	1.00
Loan Amount	74,428,003	1.1e+05	61034	67600	1.0e+05	1.5e+05
Loan Maturity	74,428,003	33.77	6.99	36.00	36.00	36.00
Monthly Income	73,354,874	18909	14663	7500	15000	35000

Notes: This table shows the Number of Observations (1), Mean (2), Standard Deviation (3), and quartiles (4)-(6) of the following variables. Suboptimal is a binary variable equals 1 if the investor made a suboptimal financial decision in terms of risk and profitability, 0 otherwise. Suboptimal_2 is a binary variable equals 1 if the investor made a suboptimal decision in terms of profitability, 0 otherwise. Bid Number is the cumulative number of bids that investors attempted. Active Time is the active time (in days) spent in the market. Overall Time is the overall time spent on the market (days). Closed Bids is the cumulative number of successful investments. Bidders is the number of bidders on loan. DTI Ratio is the debt-to-income ratio for borrowers. Gender is a dummy variable that indicates 1 = Male, 0 = Female. A loan Amount is the amount requested to fund a loan. Loan Maturity is the maturity of the loan in months. Monthly Income is the monthly income of borrowers.

Table 4.1 presents the descriptive statistics for the whole sample. We measure suboptimal decisions using two indicators. First, *Suboptimal* is a dummy variable that equals 1 if an investor attempted a suboptimal financial decision, 0 otherwise. This measurement is assessed based on both profitability and risk. Table 4.1 shows that investors on Renrendai.com make suboptimal financial decisions by 66% on average. This infers these decisions attempted by lenders are considered unsound. Therefore, this will lead to bad decision-making. The following variable, which will be used as a proxy for the main decision-making indicator, is *Suboptimal_2* and is a dummy variable that equals to 1 if investor attempted a suboptimal decision in terms of profitability only, 0 otherwise. This variable shows that individuals on the platform on average make a suboptimal decision by 70%. This again shows slight evidence of how these investors behave on the market.

Experience is measured in different ways and is split into four indicators that are: *Bid Number, Active Time, Overall Time,* and *Closed Bids*. The average number of bids on the platform is 386 bids, suggesting that investors excessively bid on this platform. The high standard deviation of approximately 736 bids indicates investor heterogeneity where investors showcase different bidding beliefs. Moreover, the average active time spent on the market is 122 days, and the average overall time spent on the market is approximately 457 days. It seems that individuals on this platform, on average, spend much time being inactive. Additionally, the average number of closed bids done on this platform is 207 successful bids. This means that investors are successful in judging based on the variation in the variable.

On average, loans on this platform have 129 bidders to fund the loan. Borrowers have a debt-to-income ratio (DTI) of 32% on average. Although borrowers on this platform might have a high debt-to-income ratio, they still have 0 outstanding debt in their balance. Therefore, loans associated with 0 outstanding debt are more likely to get funded because investors will be confident in investing in that loan. Furthermore, 63% of the loans listed on the platform are by male borrowers. Most of the loans on Renrendai.com seem to be long-term loans as Maturity averages 34 months approximately. In particular, borrowers on this platform seem to increase the number of months to repay a loan to have lower monthly repayment fees. This can also be good for investors as they will have consistent, long-term returns.

Table 4.2: Descriptive statistics, human investors

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Obs.	Mean	Std	P25	P50	P75
Suboptimal	3,0389,24	0.52	0.50	0.00	1.00	1.00
Suboptimal_2	3,0389,24	0.61	0.49	0.00	1.00	1.00
Bid Number	3,0389,24	294.61	547.70	28.00	106.00	325.00
Active Time	3,0389,24	103.11	148.99	10.00	42.00	134.00
Overall Time	3,0389,24	429.44	447.09	70.00	281.00	659.00
Closed Bids	3,0389,24	219.71	396.62	22.00	85.00	248.00
Funders	3,0389,24	34.62	51.13	9.00	19.00	40.00
DTI Ratio	3,013,570	0.44	2.12	0.12	0.24	0.40
Gender	3,0389,24	0.73	0.44	0.00	1.00	1.00
Loan Amount	3,0389,24	86694	1.5e+05	40500	68100	96200
Loan Maturity	3,0389,24	24.97	11.84	12.00	24.00	36.00
Monthly Income	3,013,570	18216	15963	7500	15000	35000

Notes: This table shows the Number of Observations (1), Mean (2), Standard Deviation (3), and quartiles (4)-(6) of the following variables for human bidders. Suboptimal is a binary variable equals 1 if the investor made a suboptimal financial decision in terms of risk and profitability, 0 otherwise. Suboptimal_2 is a binary variable equals 1 if the investor made a suboptimal decision in terms of profitability, 0 otherwise. Bid Number is the cumulative number of bids that investors attempted. Active Time is the active time (in days) spent in the market. Overall Time is the overall time spent on the market (days). Closed Bids is the cumulative number of successful investments. Bidders is the number of bidders on a loan. DTI Ratio is the debt-to-income ratio for borrowers. Gender is a dummy variable that indicates 1 = Male, 0 = Female. Loan Amount is the amount requested to fund a loan. Loan Maturity is the maturity of the loan in months. Monthly Income is the monthly income of borrowers.

Table 4.2 presents the summary statistics of manual or self-directed bidders on the platform. From this table, we notice that investors make better investments than the overall sample size, including self-directed and automated biddings. Additionally, manual bidders are likely to be associated with high debt-to-income borrowers and a high percentage of male borrowers that is 73%. This can tell us that investors on the platform, on average, prefer to associate their investments with male borrowers rather than female ones. However, this is not our main concern. Instead, we want to look at the behaviour of investors based on the level of experience that they have on Renrendai.com further. By judging investors based on their experience level, we can tell how they are behaving as they mature on the market.

Table 4.3: Descriptive statistics by experience on the platform

	Less than 90 days		**Between 90 and 180 days**		**Between 180 and 360 days**		**More than 360 days**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Suboptimal	0.45	0.50	0.56	0.50	0.67	0.47	0.80	0.40
Suboptimal_2	0.51	0.50	0.72	0.45	0.84	0.37	0.95	0.22
Bid Number	86.12	148.64	324.68	224.33	650.49	451.77	1617.74	1130.02
Active Time	25.54	24.63	128.99	25.85	252.97	50.57	533.84	160.64
Overall Time	213.10	255.37	616.31	334.02	890.06	357.29	1311.22	372.82
Closed Bids	75.26	142.04	257.74	193.25	464.00	312.49	1103.27	863.07
Bidders	35.98	55.02	34.73	49.06	30.72	38.52	27.98	30.84
DTI Ratio	0.48	2.35	0.43	2.04	0.34	1.19	0.27	0.47
Gender	0.75	0.43	0.71	0.45	0.69	0.46	0.66	0.47
Loan Amount	87622	1.6e+0	89991	1.4e+05	82947	88659	77119	46333

Loan Maturity	22.65	11.80	27.82	11.32	30.15	10.13	32.11	8.48
Monthly Income	18873	16535	17278	15397	16551	14370	16691	13480

Notes: Notes: This table shows the Mean (1), Standard deviation (2) of the following variables in four-time sub-samples. Suboptimal is a binary variable equals 1 if the investor made a suboptimal financial decision in terms of risk and profitability, 0 otherwise. Suboptimal_2 is a binary variable equals 1 if the investor made a suboptimal decision in terms of profitability, 0 otherwise. Bid Number is the cumulative number of bids that investors attempted. Active Time is the active time (in days) spent in the market. Overall Time is the overall time spent on the market (days). Closed Bids is the cumulative number of successful investments. Bidders is the number of bidders on loan. DTI Ratio is the debt-to-income ratio for borrowers. Gender is a dummy variable that indicates 1 = Male, 0 = Female. Loan Amount is the amount requested to fund a loan. Loan Maturity is the maturity of the loan in months. Monthly Income is the monthly income of borrowers.

Table 4.3 presents the summary statistics of manual bidders based on the level of experience that they have. The table shows us that as investors become more experienced, picking better-performing loans decreases. This is evident from column 1 to 8 as the efficiency in making decisions increase gradually for both *Suboptimal* and *Suboptimal_2*. Additionally, we can see that individuals associate themselves with females, lower debt to income ratio borrowers, and higher maturity loans as they become experienced on the market.

4.4. Methodology

This section introduces the methodology of this study. In this section, we show how to measure suboptimal financial decisions and introduce the econometric specification.

4.4.1. Measuring suboptimal decisions

To measure decision making, we first need to a reward-to-risk ratio for investors. Reward on Renrendai.com is the interest rate that the investor will earn, and risk is the credit score of borrowers that are associated with the loan. Credit scores are risk scores that span from 0 to 245 where the greater the score the safer the investment. However, in order to fix this measurement, we need to adjust in a way to make it the higher the credit score, the riskier the investment. The main reason behind doing this is to build a credible reward-to-risk ratio. So, let risk be the risk score that is associated with a loan and is calculated as follows:

$$\text{Risk} = \text{Maximum Credit Score} - \text{Credit Score} \tag{4.1}$$

Where Maximum Credit Score is a score that equals 246, which is one unit higher than the highest score on the platform. Once we subtract the maximum score from the original credit score, the risk measurement will be created in a way that the more it deviates from 1, the riskier the investment. After adjusting the credit score, we measure loan performance using the traditional equation that equals $\left. Interest\ Rate \middle/ Risk \right.$, where Interest Rate is the return to be earned on a loan and risk is the modified credit score of the loan.

Then, to create a reward-to-risk ratio for investor, we weigh the loan performance ratio by investor's bid amount and make this measurement cumulative. This means that investor's reward to risk ratio changes based on the historical performance of individuals. Particularly, let $\mathrm{Performance}_{k,t}$ be the average investor performance (reward-to-risk) of lender *k* at time *t*. Where $\overline{\mathrm{Performance}^{w}}$ is the weighted average reward-to-risk ratio within a lender. *i* is a successful bid of lender *k* until time *t*. Therefore, the aggregate measure is computed as follows:

$$\overline{\mathrm{Performance}_{k,t}}^{w} = \sum_{t} \mathrm{Performance}_{k,i} * \frac{\mathrm{Bid\ Amount}_{k,i}}{\sum \mathrm{Bid\ Amount}_{k,i}} \tag{4.2}$$

Now, moving on to measuring the suboptimal financial decision, we do the following. Let $Decision_{i,j,t}$ be the decision made by investor *i* at time *t* on loan *j*, and $\overline{Performance^{w}}_{j,t-1}$ be investors performance (calculated in equation 4.2) for loan *j* at time *t -1*.

$$\mathrm{Decision}_{i,j,t} = {}^{\mathrm{Interest\ Rate}_{i,j,t}}/_{\mathrm{Risk}_{j,i,t}} - \overline{\mathrm{Performance}^{w}}_{j,t-1} \tag{4.3}$$

By checking the difference between reward-to-risk and investor performance, we can decide if the investor attempted a suboptimal financial decision by creating the following dummy variable.

$$\mathrm{Suboptimal}_{i,j,t} = \begin{cases} 0, \text{if } {}^{\mathrm{Interest\ Rate}_{i,j,t}}/_{\mathrm{Risk}_{j,i,t}} - \overline{\mathrm{Performance}^{w}}_{j,t-1} \geq 0 \\ 1, \text{if } {}^{\mathrm{Interest\ Rate}_{i,j,t}}/_{\mathrm{Risk}_{j,i,t}} - \overline{\mathrm{Performance}^{w}}_{j,t-1} < 0 \end{cases} \tag{4.4}$$

On one hand, if $Suboptimal_{i,j,t}$ had a positive value from this difference, then we infer that the investor did not attempt a suboptimal financial decision. This is since the investors invested in a loan with better, or acceptable, performance than their current performance resulting in a good decision. On the other hand, if this difference is negative, we assume the individuals attempted a suboptimal financial decision. So, Suboptimal is a binary variable if the investor attempted a suboptimal financial decision, 0 otherwise.

The same scenario will happen when measuring Suoptimal_2 variable. It will be computed as follows. Let $\overline{\mathrm{Return}^{w}}$ be the weighted average return for investors that is weighted by the bid amount. This variable is created similarly to what we did in equation 4.2 for measuring performance. The difference is that rather than taking the reward to risk, we are only taking the reward factor (Interest Rate). In order to create Suboptimal_2 dummy variable, we do the following:

$$\text{Suboptimal\_2}_{\text{i,j,t}} = \begin{cases} 0, \text{if Interest Rate}_{\text{i,j,t}} - \overline{\text{Return}^{\text{w}}}_{\text{j,t}-1} \geq 0 \\ 1, \text{if Interest Rate}_{\text{i,j,t}} - \overline{\text{Return}^{\text{w}}}_{\text{j,t}-1} < 0 \end{cases} \tag{4.5}$$

If $Suboptimal\_2_{i,j,t}$ equals 1, then we conclude that investor made a suboptimal financial decision in terms of profitability, 0 otherwise.

4.4.2. Measuring experience

To capture investors' experience, we use several measurements to make our results more robust. First, Seru et al. (2010) claimed that individual investors gain experience from making more investment decisions. According to this, Koestner et al. (2017) inferred that using the cumulative number of active trades would define experience. However, in our case, we do not have the number of trades the investors attempted, so we use a proxy, which is the cumulative number of bids. Second, existing literature argued that time spent on the market or experience could lead to less thoughtful investment decisions (see, e.g., Camerer and Lovallo, 1999; Chernenko et al., 2016; Feng and Seasholes, 2005; Korniotis and Kumar, 2011; Nicolosi et al., 2009). Therefore, we decided to measure the second and third measurements based on time spent on the market. In order to make our investigation more robust, we use the active time and overall time in the market. The active variable will consider the days that individual showed activity on the platform. The overall variable will control the overall time spent in the market, including inactive days. Finally, existing literature argued that with experience, investors tend to make fewer financial mistakes (see, e.g., Goetzmann and Kumar, 2008; Greenwood and Nagel, 2009; Ivković et al., 2008). This means that their experience made them successful, which resulted in fewer wasteful decisions. Therefore, the fourth measurement for experience is how many successful decisions this bidder had on this platform. In this way, the more successful the investor is, the more experienced the investor becomes, and vice versa. Overall bidding volume, active days, overall days, and successful investments will be our proxy measurements for experience.[42] The increase in these indicators has been linked with the increase in overconfidence.

[42] Existing studies measure experience using other ways. For age of individuals is takes as a proxy measurement for experience and found that overconfidence increases with age (e.g., Crawford and Stankov, 1996; Hansson et al., 2008; Job, 1990). However, other studies came to contradicting results (e.g., Pliske and Mutter, 1996; Touron and Hertzog, 2004). Therefore, the relation between age and overconfidence seems unclear.

4.4.3. Econometric specification

Individual investors expect to make good financial decisions when they become experienced (e.g., Chiang et al., 2011). In particular, investors dedicate their time bidding on loans to get the best possible outcome. However, this should not always be the case. Investors are likely to make less thoughtful decisions as they practice more (e.g., Chernenko et al., 2016), especially when displaying behavioural biases (e.g., Mak and Ip, 2017). Therefore, we believe that investors will make suboptimal financial decisions due to being overconfident. In a linear probability model, we run the following specification:

$$\begin{aligned}\mathrm{Decision}(\mathrm{t} \in \mathrm{Suboptimal})_{\mathrm{i,j,t}} &= \beta_0 + \beta_1 \log(\mathrm{Exp})_{\mathrm{i,j,t-1}} + \beta_2 \log(\mathrm{Bidders})_{\mathrm{j,t-1}} \\ &+ \beta_3 \mathrm{Control}_{\mathrm{i},\gamma} + \delta_{\mathrm{i}} + \varepsilon_{\mathrm{i,j,t}}\end{aligned} \quad (4.6)$$

Where the subscript *i* indicates the investor, subscript *j* the loan, and subscript *t* indicates the bid attempt. The dependant variable is a binary variable that equals to 1 if the investor attempted a suboptimal financial decision and zero otherwise. This variable is explained in detail in section 4.1. $\log(Exp)_{i,t-1}$ is the logarithm of experience plus 1 at time *t-1*. Experience is measured using four ways that are: cumulative bidding number, cumulative active time, cumulative overall time, and the cumulative number of successful investments. We expect to see a positive significance of experience on suboptimal financial decisions as investors commit are likely to be overconfident when they mature on the market. For the remaining explanatory variables, $\log(\mathrm{Bidders})_{\mathrm{j,t-1}}$controls for the number of bidders that attempted to fund loan j before lender *i* place a bid. It is measured as the logarithm of the number of bidders plus one. $Control_{i,\gamma}$ is a vector of listings attributes. These attributes or characteristics contain information about the maturity and loan size as well as the gender, monthly income, and debt-to-income ratio of borrowers. Log (*Maturity)* is the logarithm of duration plus one of the loans and is measured in the number of months. Log (*Loan Size)* is the logarithm of the fund needed plus one for the loan. Gender is a dummy variable that equals to 1 if the borrower is a male and 0 otherwise. Log (*Monthly Income)* is the logarithm of borrowers' monthly income plus one. Debt-to-Income Ratio shows the debt-to-income ratio for borrowers. δ_i is Investor fixed effects and $\varepsilon_{i,t}$ denotes time-varying errors.

In what follows, equation (4) did not capture the exact behaviour of human individuals. In our unique dataset, we have detailed information on investors who attempted manual or automated bids. So, since overconfidence is a human behaviour; we keep only the bids that human investors attempted. All variables are defined in the Online Appendix of Table TA4.12.

4.5. Empirical analysis

Tables 4.4-4.8 present our main findings from our data. We start with investigating the impact of experience on decision-making in Table 4.4. Next, table 4.5 controls only for human bids. Then, tables 4. 6, and 4.7 split experience into categories in order to inspect the change in the sign of coefficients that will tell us whether investors are learning from their history. Finally, Table 4.8 presents the robustness checks by introducing a new dependant variable that is the profitable decision proxy for decision making.

4.5.1. Experience and suboptimal decisions

Table 4.4 reports the effects of model 1. The first column treats experience as the cumulative number of bids, column 2 and column 3 measures experience as active and overall time spent on the market, respectively. Column 4 measures experience as the cumulative number of successful bids.

Table 4.4: Experience and suboptimal investments

	(1)	(2)	(3)	(4)
	Suboptimal	**Suboptimal**	**Suboptimal**	**Suboptimal**
Lag Log (Bid Number)	0.146***			
	(0.000)			
Lag Log (Active Time)		0.129***		
		(0.000)		
Lag Log (Overall Time)			0.107***	
			(0.000)	
Lag Log (Closed Bids)				0.169***
				(0.000)
Lag Log (Bidders)	0.014***	0.012***	0.012***	0.016***
	(0.000)	(0.000)	(0.000)	(0.000)
DTI Ratio	-0.017***	-0.017***	-0.016***	-0.018***
	(0.000)	(0.000)	(0.000)	(0.000)
Gender (1 = Male)	0.003***	0.003***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (Loan Size)	-0.018***	-0.020***	-0.020***	-0.021***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (Maturity)	-0.350***	-0.348***	-0.337***	-0.362***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (Monthly Income)	-0.001***	-0.001***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Observations	72,438,304	72,438,304	72,438,304	72,438,304
R squared	0.415	0.413	0.420	0.404

Notes: This table shows the effects of the following variables. The dependant variable in the four columns is Suboptimal, representing a binary variable equals 1 if the investor makes a suboptimal financial decision, 0 otherwise. The independent variable, experience, is measured in four ways and are as follows: Bid Number, Active Time, Overall Time, and Closed Bids for Columns 1, 2, 3, and 4, respectively. Lag Log (Bid Number) is the logarithm of the cumulative number of bids at bid attempt t-1. Lag Log (Active Time) is the logarithm of the active time (in days) spent in the market at bid attempt t-1. Lag Log (Overall Time) is the logarithm of overall time spent on the market (days) at bid attempt t-1. Lag Log (Closed Bids) is the cumulative number of successful investments at bid attempt t-1. Lag Log (Bidders) is the number of bidders on a loan at bid attempt t-1. DTI Ratio is the debt-to-income ratio for borrowers. Gender is a dummy variable that indicates 1 = Male, 0 = Female. Log (Loan Size) is the logarithm of the amount requested to fund a loan. Log (Loan Maturity) is the logarithm of the maturity of the loan in months. Log (Monthly Income) is the logarithm of monthly income of borrowers. Standard errors are robust at the investor and loan level. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

To capture the effect of experience in column 4, we inspect the coefficients of each indicator of experience that are presented as *Bid Number, Active Time, Overall Time,* and *Closed Bids*. The first column measures experience using the cumulative number of bidding times. The estimates show that lenders are more likely to make suboptimal financial decisions as the number of bids increases. In economic terms, 100 bids increase by investors leads to a 14.6 percentage point increase in attempting a wasteful financial decision. Existing studies back this argument by stating that an increase in investing activity allows investors to commit serious suboptimality.[43] For example, Bauer et al. (2009) showed that investors experience 1.81% monthly losses from trading options as they mature on the market. Linnainmaa (2010) investigated and argued that investors' underperformance results from unmonitored limit orders.

Next, we measure experience depending on the active time spent on the market. We find consistent results with the previous model, where the more experienced the investor is, the more likely they will attempt an unsatisfactory. This is shown on the positive significance of *Lag Log (Active Time)* in column 2. For instance, 100 active days increase on the market will result in a 12.9 increase in the probability of making a suboptimal decision by individuals. Individuals should learn from their investing activity on the market in order to enhance their portfolio performance, for example, existing works, like Linnainmaa (2011), claim that investors expect to learn by actively trading even if they incur losses. However, in our case, it seems that what is happening with lenders is the opposite. In particular, other empirical studies found evidence on the destructive influence of activity on decision-making. [44] For example,

[43] In Online Appendix of Table TA4.9, we find consistent results with Table 4.4. The difference between these two tables is that we drop those investors who made more than 10,000 bids on the platform. Additionally, in Online Appendix of Table TA4.10, we control for listings fixed effect, and we have similar results as those in Table 4.4. The effect of experience on decision-making decreased but is still firmly negatively significant. This means that when we control for Loan FE, many loan characteristics mattered for investors when making an investment decision.

[44] See Camerer and Lovallo (1999), and Feng and Seasholes (2005) for further evidence on the impact of time and its bad influence on financial decisions.

like Barber and Odean (2001), old empirical evidence found that active investor portfolios in the US underperform compared to less active ones.

Additionally, Barber et al. (2009) conducted a study on the Taiwan Stock Exchange (TSE) from 1991 to 1995 and reported that individuals who actively trade on the market are more likely to reduce their aggregate return by 3.8 percentage points per year. In a more recent study, Barber et al. (2020) showed that only less than 3% of active daily traders earn positive net returns. Also, in their study, they found out that experienced traders who attempt wasteful and unprofitable decisions are likely to continue trading and bear losses. We repeat the analysis in column 3 using the overall time spent on the market and found consistent results with the previous models.

Column 4 measures experience by considering the success factor of investors. Our results show that the investor's success is more likely to exhibit suboptimal decisions by 16.9 percent. This suggests that investors are likely to continue making unsuitable decisions even if their portfolios have witnessed success previously. Fenton-O'Creevey et al. (2011), in their book, conducted a study on 118 professional traders in investment banking institutions, and their results suggested that successful investors tend to be emotionally stable introverts who are open to new experiences. Since investors will be open to new things, they might consider new challenges that lead them to irrational decision-making.

Regarding other control variables like loan and borrower characteristics, we find some further evidence of irrationality on this platform Lag Log (Bidders) has a positive significance, indicating that investors make worse decisions when they invest in loans with a higher number of funders. Usually, higher bidders attract attention by affecting other people's decision to invest in that specific loan, and when loans have more investors bidding on them, the probability of it being funded is higher, thereby considered a safer investment. *Debt-to-Income Ratio* is negatively statistically significant with decision-making, indicating that investors make better decisions when investing in loans associated with borrowers with higher debt. Having a high debt ratio means that borrowers have a problem balancing their income. Banks and credit providers mainly issue loans to potential borrowers when they see a low debt-to-income ratio. However, this can refer us back to the irrationality of investors on this platform. Individuals seem to make better decisions when they are associated with riskier borrowers.

Next, we find evidence of better decision-making when investors affiliate themselves with female and higher financially literate borrowers. Table 4.4 shows a positive correlation between worse decision-making and gender. In particular, this means that investors make less efficient decisions when they bid on loans that males list. Additionally, the estimates suggest that individuals have better chances of making a good investment when they bid on loans posted by high monthly income borrowers. Also, we find that the *Log (Loan Size)* has a negative sign on the coefficients suggesting that investors perform better when they invest in loans that are associated with lower loan sizes. Finally, Log (*Maturity)* has a negative significance indicating that investors make better financial decisions when investing in long-term loans.

4.5.2. Human bidders and overconfidence

In the following table, we keep in our sample the manual bidders who attempted self-directed investments. This is because overconfidence is considered a human behaviour and not a bias related to machines. Therefore, we remove the information that is related to investors who used the automated toolbox on this platform.

Table 4.5: Experience and investment suboptimality for manual bids

	(1)	(2)	(3)	(4)
	Suboptimal	**Suboptimal**	**Suboptimal**	**Suboptimal**
Lag Log (Bid Number)	0.123***			
	(0.000)			
Lag Log (Active Time)		0.124***		
		(0.000)		
Lag Log (Overall Time)			0.089***	
			(0.000)	
Lag Log (Closed Bids)				0.119***
				(0.000)
Lag Log (Bidders)	0.015***	0.013***	0.013***	0.014***
	(0.000)	(0.000)	(0.000)	(0.000)
DTI Ratio	-0.017***	-0.017***	-0.017***	-0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
Gender (1 = Male)	0.015***	0.016***	0.014***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Loan Size)	-0.060***	-0.062***	-0.063***	-0.063***
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Maturity)	-0.396***	-0.401***	-0.389***	-0.393***
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Monthly Income)	0.036***	0.036***	0.037***	0.037***
	(0.000)	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Observations	2,454,870	2,454,870	2,454,870	2,454,870
R squared	0.390	0.392	0.387	0.384

Notes: This table shows the effects of the following variables for the human bidders' subsample. The dependant variable in the four columns is Suboptimal, representing a binary variable equals 1 if the investor makes a suboptimal financial decision, 0 otherwise. The independent variable, experience, is measured in four ways and is as follows: Bid Number, Active Time, Overall Time, and Closed Bids for Columns 1, 2, 3, and 4, respectively.

Lag Log (Bid Number) is the logarithm of the cumulative number of bids at bid attempt t-1. Lag Log (Active Time) is the logarithm of the active time (in days) spent in the market at bid attempt t-1. Lag Log (Overall Time) is the logarithm of overall time spent on the market (days) at bid attempt t-1. Lag Log (Closed Bids) is the cumulative number of successful investments at bid attempt t-1. Lag Log (Bidders) is the number of bidders on loan at bid attempt t-1. DTI Ratio is the debt-to-income ratio for borrowers. Gender is a dummy variable that indicates 1 = Male, 0 = Female. Log (Loan Size) is the logarithm of the amount requested to fund a loan. Log (Loan Maturity) is the logarithm of the maturity of the loan in months. Log (Monthly Income) is the logarithm of the monthly income of borrowers. Standard errors are robust at investor and loan levels. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

The only difference thing presented in Table 4.5 is that we control for only self-directed bids. We believe that if there is overconfidence behaviour, it should be due to the irrationality of human investors. So, we only control for the bids that human individuals attempted. In the four models, we find consistent results with those presented in the previous table. In particular, our estimates still suggest that investors who become more experienced are likely to make bad financial decisions. However, in this section, we argue that this irrationality in decision-making is due to the presence of overconfidence in human lenders. The four experience measurements show positive significance at a 1% level in the four columns. We know that the more experienced investors are, the more overconfident, thereby the worse the decisions attempted. In column 1, we inspect the coefficients of *Lag Log (Bid Number)* that is measured by the cumulative number of bids. We find the same results as the previous table, where bidding volume increases more suboptimal financial decisions. The magnitude of the coefficients does not seem to change a lot than when we control for the whole sample size.

Mainly, column 1 shows that a 100% bid increase by investors leads to a 12.3 percentage point increase in attempting a suboptimal financial decision by human investors. Based on theoretical models, the more investors trade, the more likely they are going to be overconfident (e.g., Caballé and Sákovics, 2003; K. Daniel et al., 1998; K. D. Daniel et al., 2001; Gervais and Odean, 2001; Kyle and Wang, 1997; Odean, 1998). These results explain why more bidding results in more severe mistakes because of showcasing overconfidence behaviour. Apart from theories, several empirical papers have backed up the theoretical models regarding trading activity and overconfidence. Glaser and Weber (2007) used survey data that matches with the historical trading records of investors, and the estimates of their study suggest that the trade activity of these individuals positively correlates with their overconfidence scores. Finally, both Biais et al. (2005) and Deaves et al. (2009) use experimental evidence to prove that a behavioural bias like overconfidence can lead individuals to attempt an extra unneeded trade and help lower the utility of investors.

As for active days, the second column controls for investors' activity on the market. Our results show that activity increases the possibility of making bad financial decisions. The economic effect, where significant, seems meaningful. For example, the second column indicates that spending 100 more active days on Renrendai.com generates approximately a 12.4 percentage point increase in worse decision making. In a related study, Grinblatt and Keloharju (2009) studied the link between activity and sensation seeking (a proxy for overconfidence) and found a positive relationship between these two indicators. Therefore, we assume that the less suitable investments attempted by investors rely again on the emergence of overconfidence as they become experienced. The same thing applies in the third column when we control for the overall days spent in the market.

Column 4 measures experience by considering the success factor of investors. Our results show that the successful investor is more likely to exhibit wasteful decisions by 11.9 percentage points. This suggests that investors are likely to continue making the same mistakes due to overconfidence as they become successful. Gervais and Odean (2001) develop a model that allows investors to take too much credit for their success. Thus, investors overweight successes when learning about their ability. Also, they found out that successful investors are overconfident. Overall, the four experience measurements that are bidding number, active time, overall time, and successful investing, are affected by overconfidence behaviour.[45] Therefore, we assume that the main reason why investors are attempting these decisions while getting more experience is due to showcasing overconfidence behaviour.

In what follows, *Log (Bidders)* is still positively statistically significant, inferring that the number of fewer investors is associated with better financial decisions. Coming to the remaining control variables, there are no substantial differences from those presented in the previous table. Looking at *Log (Loan Size)* coefficients, they are still the same. Humans, investors usually prefer loans that will bring them higher profits. Lower loan sizes are associated with higher returns and are successful in P2P lending markets (e.g., Puro et al., 2010). Moreover, since this model shows lower loan size is associated with worse decision-making, investors are attempting risky decisions with lower loan amounts. The rest of the variables remain unchanged from the previous table.

[45] See also Glaser and Weber (2007), Grinblatt and Keloharju (2009), and Deaves et al. (2010) for further evidence on overconfidence interfering in experienced investors decisions.

4.5.3. Learning from experience

In what follows, we want to inspect if investors learn from their experience on the Renrendai.com platform. Therefore, following Caglayan et al. (2021), we split our data into separate samples based on the experience investors have. In their study, they split the experience into four categories that are based on the days spent on the market. The four categories are as follows: investors spent less than 90 days, spent between 90 and 180 days, spent between 180 and 360 days, and spent more than 360 days. Next, In Table 4.7, we categorize experience based on the number of bids that investors attempted. The experience will be in categories and are as follows: less than 28 bids, between 28 and 106 bids, between 106 and 325 bids, and more than 325 bids. We choose this pattern based on the descriptive statistics in Table 2, which shows the bidding volume distribution from 25% to 75%. These two tables (4.6 and 4.7) consider human bids as it shows the real effects of a behavior like overconfidence on human investors.

Table 4.6: Learning from previous experience (Active Days)

	(1)	(2)	(3)	(4)
	< 90 Days	**90<X<180 Days**	**180<X<360 Days**	**> 360 Days**
Lag Log (Bid Number)	-0.089***	0.199***	0.273***	0.241***
	(0.000)	(0.004)	(0.004)	(0.005)
Lag Log (Bidders)	-0.012***	0.008***	0.005***	0.005***
	(0.000)	(0.001)	(0.001)	(0.001)
DTI Ratio	0.018***	-0.016***	-0.014***	-0.008***
	(0.000)	(0.000)	(0.001)	(0.001)
Gender (1 = Male)	-0.022***	0.015***	0.009***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Loan Size)	0.060***	-0.062***	-0.045***	-0.065***
	(0.001)	(0.002)	(0.002)	(0.002)
Log (Maturity)	0.424***	-0.370***	-0.340***	-0.234***
	(0.001)	(0.003)	(0.003)	(0.004)
Log (Monthly Income)	-0.033***	0.037***	0.023***	0.005***
	(0.000)	(0.001)	(0.001)	(0.001)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Observations	1,698,895	355,957	258,593	138,941
R squared	0.392	0.576	0.662	0.641

Notes: This table shows the effects of the following variables for investors with X days of experience on the platform: (1) less than 90 days, (2) 90–180 days, (3) 180–360 days, and (4) more than 360 days. The dependant variable in the four columns is Suboptimal, representing a binary variable equals 1 if the investor makes a suboptimal financial decision, 0 otherwise. The independent variable is Lag Log (Bid Number) and is the logarithm of the cumulative number of bids at bid attempt t-1. Lag Log (Bidders) is the number of bidders on loan at bid attempt t-1. DTI Ratio is the debt-to-income ratio for borrowers. Gender is a dummy variable that indicates 1 = Male, 0 = Female. Log (Loan Size) is the logarithm of the amount requested to fund a loan. Log (Loan Maturity) is the logarithm of the maturity of the loan in months. Log (Monthly Income) is the logarithm of the monthly income of borrowers. Standard errors are robust at investor and loan levels. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table 4.6 presents our results when restrict the investor's time on the market using this platform. Columns 1 to 4 capture the behaviour of those investors who have experience of less than 90 days, between 90 to 180 days (3 and 6 months), between 180 and 360 days (6 and 12 months) and greater than 360 days (more than one year), respectively. The four columns suggest that the experience coefficients' size increased when we control for human bidders. Also, our results show that investors do not learn from their previous experiences. This is shown gradually from the magnitude of the coefficients of *Lag Log (Bid Number)* from model 1 to 4 as the positive sign on bid number becomes more considerable. Gervais and Odean (2001) demonstrated how inexperienced and unsuccessful investors could become overconfident. This result is due to the sufficiency of learning bias, with the more active traders implying a greater sufficiency of learning bias. Thus, the biased learning developed by these authors supports the argument that experienced unprofitable individuals want to continue to trade. Usually, overconfident individuals learn from their past performance (Hirshleifer and Luo, 2001). However, on this platform, investors seem to be incorrigible when learning from past experiences. Several studies in the psychological literature show that people with experience are more likely to be overconfident than naïve individuals (see, e.g., Frascara, 1999; Heath and Tversky, 1991). Additionally, similar results have been obtained by Kirchler and Maciejovsky (2002) as they show that the degree of being confident increases among individuals during asset markets experiments. Also, investigations conducted by other studies (e.g., Glaser and Weber, 2007) show that professional traders are more overconfident than naive ones, and the naïve individuals are measured by being a student.

Table 4.7: Learning from previous experience (Bidding Volume)

	(1)	(2)	(3)	(4)
	< 28 Bids	**28<X<106 Bids**	**106<X<325 Bids**	**> 325 Bids**
Lag Log (Bid Number)	-0.044***	0.094***	0.171***	0.237***
	(0.001)	(0.002)	(0.002)	(0.002)
Lag Log (Bidders)	-0.009***	0.008***	0.010***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
DTI Ratio	0.018***	-0.017***	-0.017***	-0.014***
	(0.000)	(0.000)	(0.000)	(0.001)
Gender (1 = Male)	-0.021***	0.021***	0.017***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Loan Size)	0.050***	-0.067***	-0.061***	-0.068***
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Maturity)	0.423***	-0.426***	-0.412***	-0.346***
	(0.002)	(0.002)	(0.002)	(0.002)
Log (Monthly Income)	-0.026***	0.036***	0.035***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)

Investor Fixed Effect	Yes	Yes	Yes	Yes
Observations	618,571	654,993	619,713	555,008
R squared	0.418	0.478	0.518	0.513

Notes: This table shows the effects of the following variables for investors with X bids attempted on the platform: (1) less than 28 bids, (2) 28-106 bids, (3) 106-325 bids, and (4) more than 325 bids. These patterns are based on the descriptive statistics of human bidders. The dependant variable in the four columns is Suboptimal, representing a binary variable equals 1 if the investor makes a suboptimal financial decision, 0 otherwise. The independent variable is Lag Log (Bid Number) and is the logarithm of the cumulative number of bids at bid attempt t-1. Lag Log (Bidders) is the number of bidders on loan at bid attempt t-1. DTI Ratio is the debt-to-income ratio for borrowers. Gender is a dummy variable that indicates 1 = Male, 0 = Female. Log (Loan Size) is the logarithm of the amount requested to fund a loan. Log (Loan Maturity) is the logarithm of the maturity of the loan in months. Log (Monthly Income) is the logarithm of the monthly income of borrowers. Standard errors are robust at investor and loan levels. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

In Table 4.7, we choose another pattern that is entirely based on the bidding volume. The variation in coefficients from column 1 to column 4 is similar to Table 4.6. As bidding attempts increase, investors make more poor decisions. It means that inexperienced investors make have better financial outcomes than experienced individuals at the first stages of investing. This is because being experienced does not mean being better at making decisions. For instance, experienced bidders do not necessarily perform better than inexperienced bidders (Deltas and Engelbrecht-Wiggans, 2005; Ward and Clark, 2002). Also, as investors bid more, they attempt more investment with poor performance. This is shown on the 4th column where we control for investors that bid more than 325 times on the platform. In the 4th column, Lag Log (Bid Number) records a coefficient of 0.237 where a 100% change in the number of bids generates a 23.7 percentage point change in making a suboptimal financial decision. Therefore, one might argue that this is due to overconfidence and overinvesting as previous literature claimed that these two indicators are positively correlated with each other. This is a channel that we are trying to use in order to explain our results as being experienced should result in better financial outcomes. However, in this case, it seems that there are other factors that are interfering.

4.5.4 Robustness check

So far, our results show that investors with experience are less efficient when it comes to making decisions because of being overconfident. Nevertheless, we want to investigate whether it is true furtherly. In some cases, experienced investors make decisions that do not reach the standards. What is meant by that is when investors are considered experienced, one should look at them as individuals who attempt good, or at least rational, financial decisions in terms of profitability. So, certain investors, especially experienced ones, are more likely to make unprofitable investment decisions (e.g., Barber et al., 2009). Using the fixed effect panel approach, we estimate the following:

$$\text{Suboptimal\_2}_{i,j,t} = \beta_0 + \beta_1 \log(\text{Exp})_{i,j,t-1} + \beta_2 \text{BidNo}_{j,t-1} + \beta_3 \text{Control}_{i,\gamma} + \delta_i + \varepsilon_{i,j,t} \quad (4.7)$$

Where the subscript *i* indicates the investor, subscript *j* indicates the loan, and subscript *t* indicates the bid attempt. The dependent variable is calculated in the same way as the previous models' decision and displays the suboptimal profitable financial decision. The difference in this one is that rather than taking the difference between loan and investor performance, we measure using the difference between loan returns at time t and investor weighted average returns at time t - 1. The remaining variables are the same as the ones in equation (4.6). Thus, we expect to see a negative sign on all experience coefficients.

Table 4.8: Robustness check

	(1)	(2)	(3)	(4)
	Suboptimal_2	**Suboptimal_2**	**Suboptimal_2**	**Suboptimal_2**
Lag Log (Bid Number)	0.167***			
	(0.000)			
Lag Log (Active Time)		0.172***		
		(0.000)		
Lag Log (Overall Time)			0.124***	
			(0.000)	
Lag Log (Closed Bids)				0.170***
				(0.000)
Lag Log (Bidders)	-0.000	-0.003***	-0.003***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
DTI Ratio	0.001***	0.000**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Gender (1 = Male)	-0.021***	-0.021***	-0.023***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Loan Size)	0.045***	0.043***	0.041***	0.040***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (Maturity)	-0.340***	-0.350***	-0.333***	-0.341***
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Monthly Income)	0.005***	0.005***	0.006***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Observations	2,454,870	2,454,870	2,454,870	2,454,870
R squared	0.369	0.379	0.369	0.365

Notes: This table shows the effects of the following variables for the human bidder's subsample. The dependant variable in the four columns is Suboptimal_2 representing a binary variable equals 1 if the investor made a suboptimal profitable decision, 0 otherwise. The independent variable, experience, is measured in four ways and is as follows: Bid Number, Active Time, Overall Time, and Closed Bids for Columns 1, 2, 3, and 4, respectively. Lag Log (Bid Number) is the logarithm of the cumulative number of bids at bid attempt t-1. Lag Log (Active Time) is the logarithm of the active time (in days) spent in the market at bid attempt t-1. Lag Log (Overall Time) is the logarithm of overall time spent on the market (days) at bid attempt t-1. Lag Log (Closed Bids) is the cumulative number of successful investments at bid attempt t-1. Lag Log (Bidders) is the number of bidders on loan at bid attempt t-1. DTI Ratio is the debt-to-income ratio for borrowers. Gender is a dummy variable that indicates 1 = Male, 0 = Female. Log (Loan Size) is the logarithm of the amount requested to fund a loan. Log

(Loan Maturity) is the logarithm of the maturity of the loan in months. Log (Monthly Income) is the logarithm of the monthly income of borrowers. Standard errors are robust at investor and loan levels. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

The results reported in Table 4.8 supports the findings reported in the previous sections. In particular, the four experience measurements are positively associated with the new decision-making proxy, which is *Suboptimal*_2. For example, investors who place extra 100 bids are likely to increase the probability of making a less than expected profitable decision by 16.7 percentage points. Additionally, in column 2, 100 days increase in investors' activity is associated with a 17.2 percentage points increase in attempting a profitable suboptimal decision. As for the overall time spent on the market in column 3, the coefficient's size and magnitude are less effective than active days but are still strongly significant at the 1% level. Moreover, 100 successful bids increase in investor’s portfolio leads to a 17 percentage points increase in misestimating a profitable investment. These findings suggest that investors' experience induced a drop in the efficiency in making a profitable decision.[46]

4.6. Conclusion

The first P2P lending platform was founded in 2005 and has started to develop gradually since then. It offered loans to individuals who found hardships to get loans from banks and became an investment opportunity for investors. Although recent studies covered many behavioural biases in the P2P lending market, some gaps still need to be filled, like overconfidence behaviour. Overconfidence has been and still is considered as a viable explanation for several practical situations in financial markets. Therefore, do Renrendai investors learn from their previous performance? If not, is it due to behavioural biases such as overconfidence? To illustrate more on this question, we investigate the relationship between investor's experience and decision-making on a P2P lending platform. Using data from a leading P2P lending platform in China, Renrendai.com, we provide evidence of the negative relationship between experience and decision making. In particular, we show that experienced individuals are likely to make suboptimal decisions due to the emergence of overconfidence behavioural bias.

Our study shows that there is extensive evidence of the existence of overconfidence among investors on Renrendai.com. By taking several measurements for experience, we show that although experienced investors can use their knowledge to make good decisions,

[46] In Online Appendix of Table TA4-11, we control for listings fixed effect and we find consistent results with those reported in Table 4.8. The size of the coefficients decrease compared to Table 4.8. This implies that listings fixed effect control for heterogeneity of investors.

overconfidence can interfere and make them commit costly decisions. Additionally, human users on this platform seem to not learn from their previous failures. When they are naïve, individuals seem to make fewer unjustifiable investment-related decisions than when they mature on the market. Also, investors on this platform misestimate the profitability of loans as they invest in loans that have lower returns than their portfolio performance. This can affect the performance of their portfolio negatively.

This study contributes to the literature of behavioural determinants of investor's decision-making. Previous studies (e.g., Odean ,1998, 1999; Barber and Odean, 2000, 2001) investigate the impact of overconfidence on the performance of individuals and found that overconfidence allows investors to overinvest thereby bear losses. More recent literature (e.g., Jiang and Verardo, 2018) investigates the impact of herding on investor's performance. This study has shown that herding can let investors underperform. However, other factors, such as optimism, overreaction, and expert imitation, can affect investor's behavior (See e.g., Lobe and Rieks, 2011; Farag, 2014; Gao et al., 2020). Our paper this strand of literature by showing that overconfidence interferes in investor's line of judgment.

This paper relates to the literature on learning from experience. Previous studies investigated the behaviour of investors and found out that there are behavioural motives and learning can explain the weird investments that individuals attempt (e.g., Seru et al., 2010; Linnainmaa 2011; Barber et al., 2020). Our paper relates to this literature by showing that experienced investors do not learn from their previous experiences.

Third, this paper relates to the literature on over-investing. Starting with theoretical models (e.g., Odean 1998; Kyle and Wang 1997), it has been known that overconfidence and overinvesting are positively related. This relationship has led to a deterioration in the portfolio performance of investors. Additionally, empirical studies have found the same results (e.g., Barber et al., 2009, Barber et al., 2020). Our paper complements this strand by showing that more bidding increases overconfidence, leading to increased suboptimal decisions.

Online Appendix A

Table TA4.9: Experience and investment suboptimality

	(1)	(2)	(3)	(4)
	Suboptimal Decision	**Suboptimal Decision**	**Suboptimal Decision**	**Suboptimal Decision**
Lag Log (Bid Number)	0.320***			
	(0.000)			
Lag Log (Active Time)		0.289***		
		(0.000)		
Lag Log (Overall Time)			0.202***	
			(0.000)	
Lag Log (Closed Bids)				0.423***
				(0.000)
Lag Log (Bidders)	-0.034***	-0.027***	-0.033***	-0.035***
	(0.000)	(0.000)	(0.000)	(0.000)
DTI Ratio	0.151***	0.152***	0.148***	0.154***
	(0.000)	(0.000)	(0.000)	(0.000)
Gender (1 = Male)	-0.007***	-0.007***	0.000	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (Amount Requested)	-0.053***	-0.049***	-0.047***	-0.047***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (Maturity)	0.939***	0.936***	0.902***	0.978***
	(0.000)	(0.000)	(0.000)	(0.000)
Log (Monthly Income)	0.024***	0.025***	0.010***	0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Observations	71,066,886	71,066,886	71,066,886	71,066,886
R squared	0.077	0.077	0.076	0.077

Notes: This table shows the effects of the following variables for investors that attempted more than ten bids. The dependant variable in the four columns is Suboptimal, representing a binary variable equals 1 if the investor makes a suboptimal financial decision, 0 otherwise. The independent variable, experience, is measured in four ways and are as follows: Bid Number, Active Time, Overall Time, and Closed Bids for Columns 1, 2, 3, and 4, respectively. Lag Log (Bid Number) is the logarithm of the cumulative number of bids at bid attempt t-1. Lag Log (Active Time) is the logarithm of the active time (in days) spent in the market at bid attempt t-1. Lag Log (Overall Time) is the logarithm of overall time spent on the market (days) at bid attempt t-1. Lag Log (Closed Bids) is the cumulative number of successful investments at bid attempt t-1. Lag Log (Bidders) is the number of bidders on loan at bid attempt t-1. DTI Ratio is the debt-to-income ratio for borrowers. Gender is a dummy variable that indicates 1 = Male, 0 = Female. Log (Loan Size) is the logarithm of the amount requested to fund a loan. Log (Loan Maturity) is the logarithm of the maturity of the loan in months. Log (Monthly Income) is the logarithm of the monthly income of borrowers. Standard errors are robust at the investor and loan level. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table TA4.10: Suboptimal decisions (Listing FE)

	(1)	(2)	(3)	(4)
	Suboptimal Decision	**Suboptimal Decision**	**Suboptimal Decision**	**Suboptimal Decision**
Lag Log (Bid Number)	0.110***			
	(0.000)			
Lag Log (Active Time)		0.117***		
		(0.000)		
Lag Log (Overall Time)			0.057***	
			(0.000)	
Lag Log (Closed Bids)				0.127***
				(0.000)
Lag Log (Bidders)	0.113***	0.034***	0.038***	0.118***
	(0.000)	(0.000)	(0.000)	(0.000)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Listing Fixed Effect	Yes	Yes	Yes	Yes
Observations	73,444,742	73,444,742	73,444,742	73,444,742
R squared	0.720	0.724	0.717	0.720

Notes: This table shows the effects of the following variables when controlling for investor and listings fixed effects. The dependant variable in the four columns is Suboptimal Decision, representing a binary variable equals 1 if the investor makes a suboptimal financial decision, 0 otherwise. The independent variable, experience, is measured in four ways and are as follows: Bid Number, Active Time, Overall Time, and Closed Bids for Columns 1, 2, 3, and 4, respectively. Lag Log (Bid Number) is the logarithm of the cumulative number of bids at bid attempt t-1. Lag Log (Active Time) is the logarithm of the active time (in days) spent in the market at bid attempt t-1. Lag Log (Overall Time) is the logarithm of overall time spent on the market (days) at bid attempt t-1. Lag Log (Closed Bids) is the cumulative number of successful investments at bid attempt t-1. Lag Log (Bidders) is the number of bidders on loan at bid attempt t-1. Standard errors are robust at the investor and loan levels. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table TA4.11: Extra check, Suboptimal_2 (Listing FE)

	(1)	(2)	(3)	(4)
	Suboptimal_2	**Suboptimal_2**	**Suboptimal_2**	**Suboptimal_2**
Lag Log (Bid Number)	0.069***			
	(0.000)			
Lag Log (Active Time)		0.073***		
		(0.000)		
Lag Log (Overall Time)			0.052***	
			(0.000)	
Lag Log (Closed Bids)				0.071***
				(0.000)
Lag Log (Bidders)	-0.019***	-0.017***	-0.016***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
Investor Fixed Effect	Yes	Yes	Yes	Yes
Listing Fixed Effect	Yes	Yes	Yes	Yes
Observations	2,450,860	2,450,860	2,450,860	2,450,860
R squared	0.724	0.724	0.725	0.724

Notes: This table shows the effects of the following variables when controlling for investors and listings fixed effects for human bidders. The dependant variable in the four columns is Suboptimal_2, representing a binary variable equals 1 if the investor made a suboptimal decision in terms of profitability, 0 otherwise. The independent variable, Lag Log (Experience), is measured in four ways and are as follows: Bid Number, Active Time, Overall Time, and Closed Bids for Columns 1, 2, 3, and 4, respectively. Lag Log (Bid Number) is the logarithm of the cumulative number of bids at bid attempt t-1. Lag Log (Active Time) is the logarithm of the active time (in days) spent in the market at bid attempt t-1. Lag Log (Overall Time) is the logarithm of overall time spent on the market (days) at bid attempt t-1. Lag Log (Closed Bids) is the cumulative number of successful investments at bid attempt t-1. Lag Log (Bidders) is the number of bidders on loan at bid attempt t-1. Standard errors are robust at the investor and loan levels. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

Table TA4.12: Variable's definition

Variable	Description
Suboptimal	Is a binary variable equals 1 if the investor makes a suboptimal financial decision, 0 otherwise.
Suboptimal_2	Is a binary variable equals 1 if the investors attempted a suboptimal financial decision in terms of profitability, 0 otherwise.
Bid Number	Represents the number of bids that investors attempted.
Active Time	Represents the active days spent investing on the platform.
Overall Time	Represents the overall days spent investing on the platform.
Closed Bids	Represents the number of successful investments the investors had.
Bidders	Represents the number of bidders that funded a loan
DTI Ratio	Represents the debt-to-income ratio of borrowers.
Gender	Represents the gender of borrower. This variable is a dummy variable that equals to 1 if the borrower is a male, 0 otherwise.
Loan Amount	Represents the requested amount of the loan.
Loan Maturity	Represents the maturity (months) of the loan.
Monthly Income	Represents the monthly income of borrowers.

Notes: This table displays the definition of the variable.

Chapter 5. Conclusion

5.1 Summary

This thesis focuses on several essential determinants of investors' behaviour that currently receive limited attention from the existing literature in online lending markets. In the first chapter, we introduce a critical determinant of behavioural finance, namely portfolio performance, by exploiting the online bidding data of investors. Particularly, we employ precise proxy measurement for portfolio performance that is weighted by investors' bid amounts and a dataset that covers a massive number of investors and loan listings during an extended period. The unique measurement of performance, coupled with the comprehensive dataset, provides a unique opportunity to document the essential role of past portfolio performance and its effects on the extent of adopting an automated online financial tool.

The findings from our fixed effects models suggest that past performance affects investors' decisions to use the auto-investing tool in microlending markets. That is, investors with low-performing portfolios tend to change their mode of bidding by adopting the auto-investing tool. Notably, Renrendai.com platform allows individuals to use the automated bidding mode provided to clients to manage their portfolios. So, after investors start to underperform, they tend to switch to the auto-bidding toolbox to enhance their portfolio performance. However, some individuals in the market want to rely on themselves rather than on machine intelligence. The findings of this paper suggest that good-performing investors prefer making decisions themselves in the self-directed mode. This finding shows support for the theory that claims that machines are better at decision-making than humans. This is since algorithms are created in a way to process more information in less time than humans, which lets machines be a preferable side when making decisions. Also, emotions such as fear can interfere in human decisions, whereas machines do not have artificial consciousness.

Moreover, our results confirm that investors' experience, measured by their activity on the market, can also be significant in deciding individuals' mode of investing. Particularly, we find that the longer time investors spend bidding on the market, the more likely they switch to the automated bidding tool. This indicates that more active days spent on the market result in investors relying more on the automated bidding service. Once investors try this service, they want to use it more frequently. Our findings also suggest that less experienced investors are more likely to switch to the manual mode. When they are considered naïve or inexperienced, individuals want to look for ways to generate money quickly, ignoring most fundamentals of investing. Renrendai offers the auto bidding service to their clients to manage their portfolios by making the portfolio more consistent but not more profitable. Therefore, immature investors try to distance themselves from such services because they do not generate abnormal returns.

Furthermore, we also document the indiscriminate practices attempted by the automated bidding service. Our estimates suggest that the auto-bidding toolbox does not discriminate against borrowers with specific characteristics. Machines seem to fund borrowers with the following characteristics: being female, less financially literate, and unmarried. These characteristics have been known to not attract funders over the years. Investors prefer borrowers with the opposite characteristics than the previously listed ones because individuals believe that borrowers will be more capable of repaying the loan.

In the second chapter, we investigate the response of borrowers and investors to a regulatory reform that increased the flow of money. We employ the 2017 Chinese financial regulation as a trigger of a disruption event in China. The main reason behind the 2017 financial regulation is that the Chinese government started to have growing concerns regarding the substantial capital outflows. The government is trying to get the economy back on track and maintain currency stability without depleting the country's foreign exchange reserves by implementing this regulatory reform. As a result, the total money flow in China increased after the regulation was announced, and investors started to invest more money inside the country rather than outside of China.

Besides this well-identified quasi-natural experiment, we use a comprehensive dataset of loan listings from the Chinese lending platform, Renrendai.com. This dataset enables us to investigate the event's impacts on borrower's loan listings and provides valuable insight into how investors respond to the shock. We document that investors were instantly influenced by the funding shock, leading to a significant decline in the loans' concentration. Investors display this drop in interest towards bidding on loans due to the reduction in returns that borrowers offer on loans. Since the financial regulation puts restrictions on overseas transfers, investors in China have higher chances of investing their money. Therefore, the borrowers took advantage of the reform by decreasing the interest rates set on loans. Also, borrowers increase loan maturity, meaning their repayment duration has increased, whereas the monthly repayment fees decreased.

The third and final empirical chapter contributes to the literature on determinants of investors' behaviour by revealing how overconfidence interferes in experienced investor's line of judgment and lets them attempt worse financial decisions. This chapter employs the same dataset that is used in the previous empirical chapters. The uniqueness of this data is that it has detailed information concerning bids attempted by investors and loans that borrowers list.

Our main finding is that experience alone is not enough for investors to excel in online lending markets. Sometimes, other things can shape the financial outcome, depending on individuals' behavioural biases. For example, by taking several measurements for experience, which are also considered an indicator of overconfidence, we show that experienced investors fail to make good investment decisions due to overconfidence.

Additionally, we contradict the literature of learning from experience by investigating the behaviour of experienced investors in microlending markets. Existing works have shown that with experience, investors tend to become better and learn from their previous failures. However, in this study, human users seem to not learn from their previous experience on *Renrendai.com*. When they are naïve, individuals make suboptimal decisions. But, when they become more experienced, individual lenders are likely to make more unsatisfactory decisions compared to when they were considered inexperienced on the platform. Also, investors on this platform misestimate the profitability of loans as they invest in loans that have lower returns than their portfolio performance. This can affect the performance of their portfolio negatively.

5.2 Potential Beneficiaries

This study is relevant for a range of users including both academics and policymakers. FinTech markets, although they are technological and developed, are moving at a fast pace in order to provide more services for their customers. One of the recent technological advances that they are providing for their clients is adopting robo-advising tools. It offers several key empirical contributions to the current academic research in economics and finance. First, identifying ways for improving the portfolio performance of investors (e.g., through adopting the automated bidding tool). The key findings of the first empirical chapter are that robo-advising helps investors become better performers on Renrendai.com. The platform itself can provide extra information for lenders in case they sign for the robo-advising service. In particular, Renrendai can show them the research that is done on their automated tool which can provide a better idea for investors on what to expect from such service. So, both the platform and investors will benefit from this research. Additionally, policymakers might be interested in the findings of the first empirical chapter as our findings show how easy the transition to automation might be as well as the benefits of adopting the robo-advising tool. Policymakers would also benefit from this research by seeing that robo-advisors are objective and transparent as they are less likely to discriminate against a specific group of people. So, this automated service has the capabilities to provide unbiased advice to customers and can be adjusted to client's needs. Regulatory agencies already started to look at these robo-advising tools from different perspectives as they started to issue reports about them. So, regulators started to think seriously about how they can adopt such services as well. By reading research like the ones we provide, regulators would develop the knowledge in order to supervise robo-advisors effectively.

The second empirical chapter provides some vital information for borrowers. For example, borrowers need to understand how investors think when disruption events happen. The 2017 financial regulation set restrictions on Chinese individuals who want to make overseas transfers and transactions. Therefore, rather than attracting these individuals to invest in the P2P lending market, it seems that investor was disinterested in funding these loans due to the behaviour of borrowers. Borrowers fell in the mistake of misunderstanding the current situation and rather than attracting investors with better loan rates, they decided to decrease the return on loans, decrease loan sizes, and increase maturities. This made lenders confused as now they have more money to spend in the Chinese markets but had doubts about the behaviour of other players (e.g., borrowers). Therefore, a better understanding of the financial situations is required by both borrowers and lenders. Also, this research would benefit policymakers. Regulatory agencies will look at our second empirical chapter and notice that the regulation imposed on individuals did not boost their will to invest in the P2P lending markets. Maybe investors went into different markets but what is certain is that investors did not bid more on loans as they have better spending power. Instead, investors were less interested to invest in loans in China due to the reactions of borrowers. So, policymakers can benefit from this research by reminding them that the market is controlled by several players and not by one only.

The third empirical study also offers several practical implications. This chapter suggests that experience does not mean that investors are expected to be better performers with investment-related decisions. In fact, other economical or behavioural factors can interfere with this issue. Individual investors can benefit from this and understand what to expect from themselves when investing. It can raise awareness for such a group of people since lenders in P2P lending platforms will know that being experienced does not always mean maturity in terms of decision making. Not only it is beneficial for P2P lenders, but to investors in traditional financial markets as well.

Overall, The results of the project will be relevant to other parties other than researchers/academics in the fields of economics and finance. The objectives and results of this thesis can help regulators of the banking sector in understanding more about P2P lending and how it can affect the banking sector. Second, economists and policymakers in financial supervision also can benefit from our research in terms of understanding how individuals behave on these online lending platforms. Third, central bank authorities in China and in other countries where P2P lending is having increasing attention can benefit from the project as well as providers of P2P platforms.

5.3 Future Research

Overall, this thesis focuses on the behaviour of individuals on a P2P lending platform in China. Remarkably, this empirical study focuses on both investor and borrower-related issues on Renrendai.com. First, future research can focus on other behavioural biases that investors display in P2P lending platforms. Existing studies focus on specific behavioural biases such as herding. However, this can be extended and be further investigated by including other types of behavioural biases. Second, in terms of robo-advising, this industry is still new very few recent studies started shedding the light on it. Future work could investigate robo-advising concerning other sectors (e.g., hospitality). Third, researchers can focus on the contracts that differentiate between the usage of automation on Renrendai.com. They can split different contracts into categories and investigate the behaviour of investors that follow each contract. Fourth, future research might consider that Renrendai.com stopped operating in 2021 and need to adjust their studies based on that. Additionally, other studies can try and do some investigation on cross platforms such as linking Renrendai, PPDAI from China, and other platforms from Europe or USA. Finally, the sample size of this study stops in 2018. Although the sample size is big enough and controls for eight years of online investing, future papers can extend the sample size and reach it until 2021 as anything after 2021 cannot be obtained.

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