UNIVERSITY OF BIRMINGHAM

Essays on the Peer-to-Peer Lending Markets

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Abstract

Peer-to-peer (P2P) lending creates an environment in which lenders and borrowers are directly matched without financial intermediary. Since the first P2P platform Zopa.com was founded in 2005, it has been one of the most emerging FinTech innovations. Transparency Market Research indicates that the potential market volume of global P2P market will be worth $897.85 billion by 2024. The unsecured loans funded by individual investors play profound roles in the alternative banking system. This doctoral thesis uses three empirical chapters to investigate the P2P lending market from both lenders and borrowers perspectives.

The first chapter investigates expert bidding imitation in peer-to-peer lending platforms. Differs from herding behaviour which associates certain actions of an individual to those of the whole crowd, we question whether an individual's bidding behaviour is related to the decisions made by expert. The experts are defined as investors who either have more central roles or who spend more time or money on the network. We employ data from Renrendai.com, which contains information of about 170,000 investors who placed almost four million bids on 111,234 loan listings from 2010 to 2018. Our dataset suggests that an average investor mimics the bids of expert lenders. Inactive lenders learn top investors' lending behaviour through observational learning and then follow their actions, although they do not know the experts' identity. Finally, we show that experts rarely imitate other experts, yet they exhibit herding behaviour.

The second chapter examines the reaction of individual investors to news arrival. In particular, we explore how Spanish COVID-19 (C19) information affects decisions of European investors holding Spain originated P2P loans. This study employs loan transaction data from Bondora secondary market, one of the leading P2P lending platforms in continental European. We find that asset holders react to the ongoing Spanish official C19 announcements by reducing asset prices. Also, the higher agreement on asset valuation between sellers and buyers is attributable to the ascending infections. Interestingly, investors process more country-wide C19 information compared to regional updates. This could be explained by the insufficient European media attention to Spanish region-level C19 topics. Moreover, the lockdown enhances the negative effects of C19 crisis. In addition, the dispersion of asset valuation between sellers and buyers is constricted in response to the ongoing cases.

The third chapter uncovers the impact of public holiday on the investor attention on financing issues in P2P markets. Differs from typical financial markets such as stock and futures market,

P2P market never closes. Therefore, P2P platforms create a unique environment which allows investors to trade and invest in public holidays. Using unique datasets obtained from Renrendai.com and Bondora.com, two prominent peer-to-peer lending platforms in China and continental Europe, our estimation suggests that the celebration of holiday increases the investor inattention as the investor decision time delays during public holidays. Also, the investment performance tends to decrease under limited investor attention. The mismatch on the asset valuation between sellers and buyers on asset valuation also expands during the holidays.

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Publications

The majority of the results of Chapter 1 have been published in the following:

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The majority of the results of Chapter 2 have been submitted in the following module:

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- Module leader: Professor Alessandra Guariglia
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Introduction

This thesis includes three empirical chapters exploring some important factors affecting the investor behavioural patterns namely expert imitation, information processing and holiday distraction. These works are vital for several perspectives. Firstly, the investigation of expert imitation helps us to understand the influence of experts and opinions in a financial market. Our work extends the understanding of investor herding behaviour by identifying the influential investors from crowd based on investing intensity and network features. In particular, investors tend to follow the biddings made by investors who with higher influence or investment intensity. Secondly, examining the categorical information processing helps us to explain the behavioural foundation of attention allocation. For instance, investors tend to allocate more attention to market-wide information instead of firm-level news (e.g., Chen et al., 2017). Thirdly, investigating the investor holiday trading helps to understand the abnormal inattention in P2P markets. The holiday effect has been widely investigated as the arriving of holiday might take investor's attention away from the trading issues (e.g., Kudryavtsev, 2018; Ryu and Yu, 2021). This thesis extends the understanding of holiday effects to an environment in which holiday trading is allowed.

The first chapter titled "Expert Imitation in P2P Market" investigates the expert bidding imitation in P2P lending market. This chapter contributes to the empirical literature by different dimensions. First, this chapter is related to behavioural finance literature that discusses herding behaviour (Wei and Lin, 2016; Jiang et al., 2018). This phenomenon has been explored in P2P environment (e.g., Lee and Lee 2012), evidence of herding is also observed in this study. We further document that P2P investors observe and imitate their peers' investing decisions. Secondly, this chapter is also built on the literature on experts/opinion leaders. Influential people could promote the information transmission and affect others' actions in a community (Valente & Rogers, 1995; Watts & Dodd, 2007), as these people are considered as experts/opinion leaders. Equipped with a unique P2P environment, this chapter identifies the leaders and documents that leaders' actions impact bidding behaviour of remaining investors in the market.

The dataset employed in the first chapter is collected from Renrendai.com, one of the leading P2P lending platforms in China. The dataset contains fundraising information covers from 2010 to 2018. In particular, it involves in detailed borrower characteristics such as personal identification and financial situation, as well as loan-specific information (e.g., interest rate, requested amount and maturity). Furthermore, the bidding history for each loan is also available for investors. Therefore, each loan listing is equipped with the loan information and the record of all biddings (e.g., time label, bidding amount and investor ID).

Using this information in conjunction with the network centrality measures, we identify the most active or central investors in the Renrendai.com universe, and call them experts. Then, we examine whether experts' biddings affect the remaining investors. Our estimations provide the initial evidence that investors imitate experts' biddings. Furthermore, listing fixed effects and variables are also included to control for payoff externalities. We then document that the investor community imitate the experts behaviour: Our proxy of expert indicator exerts positively significant effects on investor bidding decisions. This study is further extended by the estimation on herding inclination. Interestingly, all investors active in the community, both experts and generals, cannot avoid herding. This finding suggests that herding might be inherent to nature of human beings.

The second chapter entitled "Asset pricing in a P2P market: the role of COVID-19 news" investigates the how pan-European investors holding Spain-originated P2P loans react to the arrival of Spanish COVID-19 information. This chapter amends the literature on investor information process by investigating how individual investors process country-wide news and region-specific information. This chapter also adds to the literature shedding light on the role of investor inattention. We link the investor inattention to the information transmission channel. This chapter documents the inattention to region-wide updates might be driven by the insufficient media attention on regional news. Last, this chapter adds to literature by estimating the C19 crisis impacts on individual investors in a P2P environment.

The comprehensive dataset employed in the second chapter is collected from several resources. First, we obtain dataset of secondary market from Bondora, one of the prominent P2P platforms in continental Europe. Each loan is equipped with unique loan identifier, borrower information and transaction history. In particular, the dataset contains transaction recordings of 12,012 loans from February 2020 to May 2020. Second, we collect confirmed case and death counts from archived Spanish Health Ministry announcements. Importantly, this chapter employs C19-related releasement on both country- and region-level, therefore we could investigate the information processing on different categories of updates.

Our results show that, C19 announcements could affect investor behavioural patterns. The baseline estimates suggest that sellers ask lower price in response to the Spain C19-case updates. Meanwhile, the market liquidity shrinks as sellers list fewer notes within the ongoing cases. Further, buyers are more likely to agree the asked price. Interestingly, investors tend to rely more on Spain-wide statistics compared to regional updates when making decisions. Additionally, our estimations suggest that the C19 announcements narrows the dispersed beliefs on the asset valuation between sellers and buyers, buyers are willing to accept the lower prices favoured by sellers.

We further explore the investor inattention to the regional C19 updates. We posit this inattention might be explained by the insignificant information transmission channel on region-level C19 topics. To proxy the transmission channel of C19 information, we obtain European Google trends indices, as well as the media coverage on C19 topics for Spain and its regions. Including the effects of C19 announcements, our estimates suggest that regional C19 news transmission channel is insignificant to investor decisions. Thus, media attention on country-specific C19 topics is significantly related to decision-making. That is, country level C19 information is more likely to be propagated, whereas the channel of C19 topics on micro region-level is inadequate. Hence, the investors might be inattentive to the region-specific C19 information.

The third chapter, "Investor Distraction during Holidays: Evidence from P2P platforms" documents that, investor trading frequency in public holiday might affected by the holiday distraction. Prior studies suggest that investor attention might be distracted around public holidays (e.g., Luboshitzky and Gaber, 2001; Dellavigna and Pollet, 2009). However, whether investors attention would be distracted during holidays is still rather limited. It is because most of financial markets close during holidays. Differs from previous studies, this chapter investigates whether there is a holiday effect in P2P lending markets that open throughout al l day and all year. Therefore, this chapter intends to investigate the holiday trading patterns in a P2P lending environment.

This chapter employs the dataset of trading recordings in Gao et al., (2021) and *Bondora* secondary market. In both datasets, all the trading records are equipped with time stamp, which allows us to observe the investor distraction pattens throughout all dates in each year. In particular, the Gao et al., (2021) dataset contains the investing records and information of 111,234 loans covers from 2010 to 2018. The unique investor identifier allows us to observe the investment of investor throughout their entire career on the market. Meanwhile, the Bondora dataset provides the transaction history, repayment history and loan information of 111,294 P2P loans covers from 2016 to 2021. Labelled with the unique loan identifier, we could observe the investor behaviour throughout the loan transaction progress.

We first investigate the investor inattention during public holidays. Our results suggest that, investors in *Renrendai* primary market tend to spend longer time to make purchase decisions during public holidays. Also, the decision time in *Bondora* secondary market increases during holidays. Indeed, investors are more distracted to investing issues during public holidays. We also exploit the drifts in investment performance and mismatched asset valuation. First, the quality of holiday investment in primary market is lower than normal trading days. Second, the mismatched belief between secondary sellers and buyers is increased in holidays. That is, investors are more carelessness in holidays, consequently, they are more likely to make inferior decisions.

We further extend the understanding of holiday distraction by exploiting the interrelation between investor's holiday distraction and level of experience on the market. Rookie investors try to maintain their investment quality although their holiday trading is delayed. In contrast, the experienced investors are also distracted by holiday issues, thus, those experienced investors are more likely to make inferior decisions compared to the rookies. We therefore document that, the holiday distraction exhibits heuristic features.

This chapter contributes to the literature focuses on the role of holiday factors in investor decision. This analysis differs in extending the understanding of holiday effect to the holiday trading days in the P2P markets. Second, this work also adds to the behavioural economics literature shedding light on the investor distraction. We document that the celebration of public holiday distracts investors, therefore the performance and investing activity are lower than normal trading days. Third, this chapter attempts to explore the connect between the investors experience on the market and the degree of holiday distraction.

Background Information

Renrendai.com, a leading P2P platform in China, was founded in October 2010; since then, it has attracted about 170,000 investors and 90,000 borrowers (Wang and Liao, 2014; Mi and Zhu, 2017). Until October 2018, when the data was collected, it has attracted more than 170,000 lenders and 90,000 borrowers. Since the platform was founded, it has gathered over 10 billion RMB funds with more than 1 million funded loans. The loan application procedure is rather straightforward: any adult borrower who holds Chinese citizenship could initiate a loan application with the amount from 3,000 RMB to 50,000 RMB.

To raise funding from the P2P market, the borrower is required to fill in a standard formatted statement which indicates the use of the loan (such as business loan, educational loan, property loan, car loan), and borrower's personal income, employment and debt information are also required. Once the platform receives the listing application submitted by the borrowers, the managers on behalf of the platform would assign a credit rating, from AA, A, B, C, D, E, F and HR, where AA reflects the most outstanding level and HR means the loan is identified as "High Risk" listing. These ratings are issued based on the borrower's uploaded information and personal statement. In general, clean credit history and solid identity would be helpful to obtain good credit-rating, whereas borrowers with defaulted history or criminal evidence might be labelled as low-rating borrower.

The loan listing will not be listed in the bidding system until the credit-rating is approved by the platform. There are three main service provided by the Renrendai.com, including manual bidding, automatic bidding and hybrid bidding services. In particular, the manual bidding give full access to investors, therefore all the investment under manual bidding service would be given by human decision only. The automatic bidding service makes investment with the authorization contract signed by the investors. The hybrid service allows the investors to choose to depend on either decision modes. In this study, we focus on the investor inattention pattens during holidays, therefore we focus on the investment given based on human volition.

Investors benefit the Renrendai transparent data public policy. First, investors are allowed to explore the information related to the loan and borrower characteristics. Investors often fund loan listings equipped with different features to diversify the idiosyncratic risk raised by the specific borrower. Second, the historical bidding recordings on each loan listing is observable to all investors who manually explore the system. Once the loan listing appears on the system, it has up to 7 days to receive the funding from investors. After 7 days, loans raised fulfilled requested amount would be tagged as successful and archived; otherwise it will be labelled as "failed" and removed from the system, the biddings amount would be returned to the accounts of investors who bid to the failed loan listings. Generally, a listing would be fulfilled within approximately 4 hours since its' appearance. After the successful loan archived, the repayment progress would be triggered: the repayment of principal and interest are transferred to a specific bank account owned by the borrower. The Renrendai platform prepared several measurements to collect the overdue repayment, such as phone call warning, physical visit and court warning. The enforcement policy leads to a very low default rate in Renrendai.

Having introduced the basics of Renrendai.com, We turn attention to the background information of Bondora.com. Founded in Estonia (2009), Bondora has become one of the leading P2P lending platforms in continental Europe. The primary market was first available to Estonian borrowers in 2009. The loan service then extended into three marketplace including Finland, Slovakia and Spain in 2013. Since Bondora launched the primary loan service, it has processed loans worth more than 300 million euros.

The requirements for both borrowers and investors are quite straightforward: any adult individual holds citizenship of a European Union country, or a country accredited by Bondora, can register and invest. In the primary loan market, to apply for a loan, a borrower is required to provide personal identification, contact number, socio-demographic information, income and liability information, as well as other supplemental information. After the application is submitted, the platform manager team evaluates both loan-specific and borrower-specific characteristics. A decision on whether the loan application can be published on the system is then issued based on the loan and borrower information. Once the application is approved, a conditional loan with a particular credit ranking is posted on the market. The investors can then explore and bid for the loans by a manual bidding system or using automatic tools provided by the *Bondora* platform. It is worth to mention that loans are created by borrowers from Estonia, Finland and Spain, while all loans are accessible to all approved countries (i.e. all EU countries together with Iceland, Liechtenstein, Norway, Switzerland and the United Kingdom).

Initially, *Bondora* only operated a primary loan service. *Bondora's* primary market mainly provides micro sized loans with a mid-term maturity.[1] Primary market investors are allowed to invest by taking their own decisions or relying on automatic tools. To help investors evaluate the loans, the platform allows investors to explore all public borrower and loan characteristics.

[1] The maturity of loans varies from 3 to 60 months. However, most of loans are 36-60 months. The size of loans varies from 500 EUR to 10,000 EUR.

These include the borrower's information (i.e. gender, age, country, region, city, employment, marital status, income, education and property ownership), loan-specific information (i.e. the requested loan amount, maturity, interest rate, purpose and credit ranking). The average loan age is 51.68 months (about 4 years). The original loan requested amount ranges from 115 Euro to 10,000 Euro, yielding an average size of 1,987 Euro. After a loan is funded, investors can observe the loan performance by monitoring the loan repayment history, including the collection date, the repayment amount and the interest payments.

In March 2013, *Bondora* launched a secondary market, encouraging investors to sell or purchase the holdings of loans (also called notes or listings) that originated from *Bondora* primary market with a discount, a premium, or par-value prices. Bondora's secondary market is rather active: for instance, in January 2020, the very last month before the C19 outbreak, it processed about 295,000 transactions worth 954,000 euros. Technically, buyers can invest based on their own decisions or rely on the portfolio manager[2]. A note cannot be sold after 30 days since its posting date, as at this point, it is labelled as "Failed" and removed from the system. On the contrary, if it is sold, it is labelled as "Successful". In addition, if sellers change their mind and cancel the selling, the note will be tagged as "Cancelled" and removed from the system.[3]

It is worth noting that retail investors benefit from the flexible, transaction-free marketplace provided by *Bondora*. First, an investor may purchase notes of a loan originated from low-risk borrower with no historical repayment problem at a premium to seek stable future repayment. But in reality, the premium price of the note might be too high compared to the potential future returns, which leads to far lower actual returns than the level expected. Second, compared to the primary market, the secondary market is more profitable but risker. Investors may buy notes of an overdue or defaulted loan at a discount to seek later repayment through the recovery process. The actual returns on those risk-taken investments generally relies on the collection and recovery process, because these loans may not receive regular repayments and the principal bought may not be fully recovered.

The secondary market provides a more profitable, but also risker investing opportunity compared to the primary market. Individual investors of Bondora secondary market could also benefit from the transaction-free marketplace and information transparency. For instance, the

[2] The portfolio manager is an automatic tool which allows investors set up their personal requirements based on loan and borrower characteristics, once there is a note matches the investors' personal investment strategy, the automatic tool will purchase the asset directly.

[3] The Bondora allows sellers withdraw their notes, however, it is not observed in the secondary market data.

loan holdings listed on the trading system are equipped with the loan information and repayment history, investors could seek loan holdings created by borrowers with sound personal background without defaulted history. However, the high-priced notes might be too expensive compared to its actual future cash flows, therefore the actual return might be lower than expected. In contrast, investors might be willing to purchase loan holdings with defaulted recording at a low price. This strategy mainly focuses the potential profit comes from the future repayment or collection progress. Currently, Bondora primary loan service is mainly operated by automatic bidding tools authorized by the investors, therefore in this study we focus the dataset generated from the secondary market trading.

Chapter 1: Expert Imitation in P2P Markets[4]

[4] This chapter has been published in an academic journal, *the Manchester School*. Gao, G., Caglayan, M., Li, Y., & Talavera, O. (2021). Expert imitation in P2P markets. *The Manchester School*, *89*(5), 470-485.

1.1 Introduction

P2P lending platforms create an environment in which individuals can directly borrow and lend without the use of intermediaries (Serrano-Cinca, Gutiérrez-Nieto, & López-Palacios, 2015). These lending platforms offer simplified procedures and lower transaction costs as compared to traditional financial markets (Collier & Hampshire, 2010), yet they also attract investors who are not well-equipped to cope with the risks associated with lending in risky markets (Lee & Lee, 2012). In such markets, a listing receives multiple bids and lenders (investors) generally contribute to multiple loans to diversify their risk (Zhang & Liu, 2012). Bidding information is recorded and visible to all platform users. Hence, besides borrower or loan characteristics, earlier bids of peers in the system can be taken as additional information by investors in the community when making new lending decisions. While the effects of previous bidding volume or herding behaviour have been explored in the previous literature (Berger & Gleisner, 2009; Caglayan et al., 2019a), little is known about the impact of the composition of the crowd on lending behaviour and whether expert imitation is observed.

The literature on expert imitation is scarce. Kahle and Homer (1985) provide early evidence that expert behaviour affects individual decisions. While experts act independently, their activities affect others, prompting a followership (Hayes-Roth, Waterman, & Lenat, 1983; Aral & Walker, 2012). Kim and Viswanathan (2018) showed that experienced investors affect crowd decisions in *Appbackr*, a crowdfunding website. In P2P lending markets, the composition of the crowd could also play an important role. In particular, when investors are not well-equipped to evaluate the risks, they may choose to mimic (replicate) the actions of those who are more experienced.

In this study, we seek evidence for the presence of expert imitation in a Chinese P2P platform, *Renrendai.com*. What we propose here is related to, yet differs from, the simple herding behaviour which associates certain actions of an individual to those of the whole crowd. In this study, we question whether an individual's bidding behaviour is related to that of an expert's bids. Yet, to investigate whether ordinary investors follow experts' actions, we must come up with an approach to identify the leaders in a P2P platform. Unlike social media celebrities, experts/leaders on P2P lending platforms are not flagged or marked. We identify a P2P investment expert as an individual who has high investment intensity, defined either by the number of bids or by the amount of investments carried out by the same individual. This approach is further extended by centrality measures from network analysis in which investors (nodes) are linked (edged) if they invested in the same loan. The strength of connection can also be measured by either the amount of investment, the number of investments, or a weighted measure of both.

To explore behavioural investment patterns in the crowd, we focus on *Renrendai.com*, one of the leading platforms in China (Yang & Lee, 2016), and extract data from 2010 to 2018. The dataset provides detailed socio-demographic and financial information about borrowers (e.g., income) as well as loan listings terms (e.g., interest rate or maturity). Furthermore, each loan listing contains the history of all biddings, including time span, amount of bid, and investor anonymized ID. Using this information in conjunction with the centrality measures mentioned above, we identify the most active or central investors in the *Renrendai.com* universe, and call them experts.

Having defined experts, we next check whether experts' decisions influence the rest of the investors on the platform. Indeed, whether the general investor could identify the biddings from experts is the research question that was asked in the very beginning of the chapter. We address the research question that whether general investors identify and follow the influential investors. In the empirical analysis, the baseline estimation is mainly designed to test this hypothesis. We first implement a simple OLS model in search of a sequential correlation. This model provides the initial evidence that investors imitate experts' bidding patterns. We then include, in our empirical models, listing fixed effects and variables to control for payoff externalities; we confirm that the investment community follows the experts: Our measure of expert indicator exerts a significant and positive effect on investors' lending behaviour. As we deepen our investigation, we further find that all investors in the P2P community, including experts, herd. This observation provides evidence that herding is inherent to human nature.

This paper draws on two strands of research. First, our work is related to behavioural finance literature that discusses herding behaviour (Berger et al., 2009; Rook, 2006; Wei & Lin, 2016). This phenomenon is explored within P2P markets. Lee and Lee (2012) find evidence of herding behaviour in *Popfunding.com*, a Korean platform. Herzenstein et al. (2010) study the strategic herding in *Prosper.com* while arguing that herding increases crowdfunding, but once the target is fully funded, herding diminishes. Zhang and Liu (2012) investigate the rational herding in *Prosper.com*, which contributes to the literature because the herding is considered an irrational mechanism. Similar to these studies, we observe evidence of herding behaviour. However, additionally, we provide evidence that investors observe and imitate their peers' bidding actions.

Our study is also built on the literature on expert/opinion leaders. Influential people are likely to promote the diffusion of information, innovation, social capital, and behaviour in a community (Chan & Misra, 1990; Valente, 1995; Burt, 1999; Watts & Dodd, 1997), as these people are identified as experts or opinion leaders. For instance, Trusov et al. (2010) provide a measure by which to detect influential people in social media based on their communication and activity and provide evidence that users can be clustered into different levels of influence in the community. Iyengar et al. (2011) combine a sociometric and self-reported measure to detect the influence of actors in the social network. They find that heavy social media users are more influential in new product diffusion. This study, within a P2P environment, identifies the leaders and shows that leaders impact bids of the remaining investors in the community.

We construct the paper as follows. Section 2 provides information about the data and the associated descriptive statistics. Section 3 lays out our methodology and the empirical model. Section 4 presents the results. The last section concludes the paper.

1.2 Expert identification

Our proxies of expert lenders are based on the count measure as well as network centrality measures. To implement the count measure, we employ two approaches. Using a four-month rolling window, we calculate (1) the total amount of investment during the first three months (we call this period the learning interval) and (2) the number of investments for each investor.[5] Then, we identify the top 15% of the investors within each proxy and generate two separate measures to identify *experts*. Count measure is straightforward and computationally-light, which provides a simple means to directly record the investment experience of members in the P2P community. However, "count" measures could not properly reflect the linkages among investors. For instance, when an investor provides funds to a loan that has a potential of 100 bidders (including this investor), the investor's action is visible to 99 investors in the community. In contrast, an investment decision on a listing that has the potential for only 10 investors to bid would be seen by only nine bidders. Practically, imitation emerges from observational learning, and observational learning requires a visible signal. If the signal is not observed by as many investors as possible, the influence of expert behaviour on the community will be limited. Hence, count measures could be a good first-choice approach, but they would not capture the extent to which an investor influences other investors in the same community.

[5] We have conducted two extra checks by allowing the rolling windows to be either three or five months; we received quantitatively similar results. The results from these exercises are available from the authors upon request.

To study how signal transmissions can affect the behaviour of investors, we next apply network centrality measures. Centrality allows us to investigate the importance or influence of prominent actors in a network (Barrat, 2004). A network contains nodes (actors) that are associated by links (ties or edges) (Otte & Rousseau, 2002). Nodes refer to individuals who have connections to other individuals; a tie represents a unique connection between two nodes (Menichetti et al., 2014). In this context, the P2P community is similar to a social network that embodies a substantial amount of information (Lin et al., 2013). In fact, investors in P2P communities are connected by the bidding signals dispatched by the investors who bid on various listings at a time.

Using *Renrendai* data, we construct a network on a monthly basis in which investors connect with others by observing and learning peers' behaviour. In particular, we construct connections between every individual *lender ID* who invests in the same *loan ID*; the connection is weighted by the bid amount, and the bid amount is the signal that the particular *lender ID* dispatches to the other *lender ID*. Given the connections and investors, we generate an edge list that records the signal (bid information), resource, target, and strength (*bid amount*). Then, we compute a degree of centrality to identify the most influential actors (investors) (Bonacich, 2007). Different measures capture the influence of actors in a network. Degree centrality, betweenness centrality, and closeness centrality are the most common choices (Bonacich, 2007). As the most basic centrality measure, degree centrality captures the number of ties to a given point, which is defined as the number of links that a node has to other nodes (Opsahl et al., 2010). Betweenness centrality captures how many times a particular node serves as a bridge on the shortest path between two other nodes (Newman, 2005). Closeness centrality captures how many ties (steps) of the shortest path are required for a specific node to connect with every other point in the network (Borgatti, 1995). In this study, we estimate degree centrality to measure the number of ties, i.e., connections, of a particular agent. This indicator reflects the extent to which an actor is important or central to a network (Herrero-Lopez, 2009). Ignoring the direction, degree centrality simply counts the number of ties for every actor, $C_D(k) = \sum_j^N X_{kj}$, where k is the focal node, j is all other nodes, N is the total number of nodes, and x is the adjacency matrix.

As defined above, the degree centrality measure considers only the number of connections that an agent holds. However, in weighted networks, each connection is associated with a weight that represents the strength of the connection (Opsahl et al., 2010). To extend the degree centrality measure, Newman (2005) and Barrat et al. (2004) introduced the weighted degree, which summarizes the weights of all connections. More specifically, $C_D^w(k) = \sum_j^N W_{kj}$, where W is the weighted matrix, in which if actor k connects with j, the associated element of the weight matrix, w_{kj}, represents the strength of the connection.

The original degree and weighted degree reflect the number of connections and the strength of the connections, respectively. To combine the number and the strength of nodes, Opsahl et al. (2010) introduced a balancing parameter, α, to their proposed measure, $C_D^{w\alpha}(k) = C_D(k)^{\alpha} C_D^w(k)^{(1-\alpha)}$. For our purposes, we weight the P2P network by the investment amount, and we extend the degree by the sum of the weight with which we summarize the bid amount. We calculate the degree centrality by number of ties $C_D(k)$ by summarizing the total number of connections that an investor has in relation to other investors. Also, we compute the degree by the weight $C_D^w(k)$, which belongs to a *lender ID,* by summarizing the *total bid amount* that the *lender ID* dispatches to all target lenders. The degree measures the result in two rankings, which represent the connection number and the connection strength. We employ both of these two rankings and identify, as experts, the top 15% of investors in the ranking.

Unlike a simple count measure, centrality measures reflect how the information is transmitted in a community.[6] In *Renrendai.com*, the historical bidding records are the only visible resource for investors to observe and learn from while the listing is active on the website. This information source disappears once the listing is completed and removed from the platform. Of course, past records are open to all lenders, but if we consider that the signals pass throughout a network, the lenders who invest in the same loan listing are most likely to observe and learn when the listing is actively receiving funds from the public. In a P2P platform, *bid amount* and *bid number* are the two visible resources. By taking both the number of connections and the strength of connections into account, we calculate a balanced degree of centrality. Assuming that the degree and the strength are equally important, we calculate the balanced degree centrality measure $C_D^{w\alpha}(k)$ for each *lender ID*. The balanced degree centrality provides our additional ranking from which we select, as the experts, the top 15% of investors with the

[6] It is worth to note that, when we identify the expert, we consider the expert imitation is a human behavioural pattern, therefore we only consider the influence of the human investors. Consequently, the automatic bidding is excluded in the influence calculation. Indeed, we also calculate the centrality and investing intensity including the automatic biddings, but the automatic bidders are very unlikely to be labelled as experts due to their low-activity. This phenomenon might be raised by the market setting of Renrendai.com. This platform offers automatic bidding service for investors who rely on the monthly salary income; therefore the investing intensity of automatic bidding service would be low.

highest balanced degree.[7] Using these centrality measures, we generate a dummy *Expert* to flag the expert investors in the P2P investor community.[8]

1.3 Data description

We collect data from *Renrendai.com* between the period from October 2010 to October 2018. Our data are constructed from two sources. Firstly, we collect loan listings information about loan and borrower characteristics. Secondly, for each loan listing, we capture the bidding records and identify the bidder for each bidding. Hence, every specific bidding record is associated with a particular *lender ID*. We combined these two resources by utilizing the *loan ID* and generated a sample containing more than 16 million observations. For a particular *loan ID*, its loan characteristics, including annual interest rate, credit ranking, requested loan amount, listing time, maturity, and duration, are recorded. The purpose of the loan application is also attached (such as car loan, property loan, education loan, business loan and education loan, etc.). The platform provides information about the borrower characteristics, including *borrower ID*, monthly income, borrower age, employment situation, residence location, educational level, immovable property ownership, and credit history on the platform. When we turn to the investors' view, we have *lender ID*, bid amount on all lists, and bidding time on each bid. Finally, for each loan listing, we construct a dummy variable to depict hourly human or hybrid bidding. Also, a pseudo panel on active bidders is constructed to investigate all active bidders' activities.

Table 1. shows the basic statistics on lenders. Our dataset records both bidding and borrowing information on 432,882 observations based on 3,947,996 bids on 111,234 listings. The average number of hourly bids is 6.44, with a standard deviation of 19.03. The wide variation of the bidding frequency may be associated with investors' daily routine, as investors may be more active at certain times of the day. In contrast, we observe that the average hourly number of bids attributable to experts is 1.88, with a standard deviation of 4.98. Furthermore, the average hourly total bid amount on the platform is 9,368 and the average expert contribution to the platform is 3,511, indicating that 37% of the investments are made by the experts. These features suggest that experts invest much more actively than do the rest, and that their

[7] We have experimented with thresholds of 10% and 20% to define experts and received quantitatively similar results. Results are available from the authors upon request.
[8] We add descriptive statistics among Expert bidding vs. Non-Expert biddings in Table TA1.7. We observe that the experts are more likely to invest in the loans with higher returns but also higher risks. This comparison suggests that the expert investing strategies might be more audacious than the non-expert investors.

investment pattern is more stable than that of the average investors, as the standard deviation associated with expert behaviour is lower.

Table 1. displays the basic descriptive statistics for all 111,234 listings in our dataset. The amount of the loan that a borrower can receive varies from 3,000 RMB to 500,000 RMB with an average of 49,142 RMB. The average interest rate is about 12.29% with a standard deviation of 2.61%. The average maturity is approximately 22 months. The platform labels 22% of the loan applications as high-risk listings. Borrowers' average debt to income ratio (DTI) is about 28% Although DTI could be very high for some of the applicants, some borrowers do not have any outstanding debt; therefore, the DTI for such applicants is calculated as 0. Having no outstanding debt gives confidence to borrowers, as lenders in China tend to prefer funding applicants who have no or little debt. Generally, a listing reaches the requested amount within approximately four hours, with a standard deviation of 17 hours. A high standard deviation on completion rates implies that some listings are very popular and are completed very fast, though other listings take longer to fill, if at all. In the first hour, a listing receives 23 bids on average. This high average suggests that investors are eager to bid on listings, or perhaps new listings do not arrive as quickly, which causes investors to race to place a bid. This makes sense, as most of the bidders are small investors and the savings rates from banks are very low.

1.4 Empirical model

To examine the claim that expert lending behaviour influences the remaining members in the investment community, we focus on the role of the cumulative historical biddings in the previous hours on investors' current bidding decisions. Indeed, our baseline estimation is designed to examine this question: whether general investors could identify those influential experts and follow the experts' movements. While doing so, we split the previous bidding information into two groups: bids received from experts and bids received from non-experts. We are interested in investors' behaviour for a specific listing after these investors have observed the number of expert bids as well as the total amount that experts invested in the previous hour. We generate cumulative hourly bidding data for each listing, from the time a listing is posted until the listing fills up or expires.

Our first approach is based on a simple OLS model and takes the following specification:

$$\begin{aligned} \textit{Hour Bid Amount}_{it} = {} & \alpha_1 \textit{ Expert Amount Percent}_{i,t-1} + \alpha_2 \textit{ Total Bid Amount}_{i,t-1} \\ & + \alpha_3 \textit{Total Bids}_{i,t-1} + X_{it}\beta_1 + Z_i\beta_2 + e_{it} \end{aligned} \tag{1.1}$$

where *Hour Bid Amount*$_{it}$ is the funding amount that loan *i* has received at time *t=1, 2, ..., 60.*[9] Although *Renrendai.com* allows every loan listing to be posted on the system for up to seven days (168 hours), we keep data on loan listings up to *T=60* hours because the average completion time on the platform is around four hours. We also observe that listings that are not funded at *T=60* hours rarely receive full funding by the end of 168 hours, or seven days. Also, as noted earlier, *Hour Bid Amount*$_{it}$ does include investments from those who join the community in the middle of a rolling window.

The OLS specification (1) allows us to check whether investors are affected by experts in the community. The key variables of interest, *Expert Amount Percent*$_{i,t-1}$ and *Hour Bid Amount*$_{i,t-1}$, gauge the percentage of lagged cumulative funding from experts and collective investors, respectively. In particular, *Expert Amount Percent*$_{i,t-1}$ represents the percentage of the cumulative amount which is attributed to experts in a listing *i* by the end of hour *t-1*.[10]

The model employs vectors X_{it} and Z_i to measure the time varying and time invariant. For vector X_{it}, *%Needed*$_{i,t-1}$ presents the percentage of the requested amount by loan *i* which is left unfunded by the end of hour *t-1*. To capture the effect of the bidding time throughout a day, we include *Hour of Day,* H_{it-1}, and *Day of Week,* D_{it-1}, as time fixed effects. Vector Z_i contains the time invariant loan characteristics, including *Requested-Amount, Maturity, Credit Risk, Debt-to-Income-Ratio,* and *Property-Ownership Dummy*. The *Start Day* is also included in Z_i to measure the opening date for the loan listing. Because our data incorporates information from both manual bidding and manual-auto-hybrid bidding services, we introduced lagged *Percent Auto Bidding* in our model to control for the effect of machine bidding for the subscribed investors. The e_{it} denotes the error term.

Model (1) could not be used to capture the presence of observational learning and imitation. This is because sequential correlation could materialize as a result of unobserved heterogeneity across loan listings. To control for unobserved heterogeneity in the data, we modify our model and introduce listing fixed effects, μ_i. The model now takes the following form:

$$\begin{aligned} \textit{Hour Bid Amount}_{it} = {} & \alpha_1 \textit{ Expert Amount Percent}_{i,t-1} + \alpha_2 \textit{ Total Bid Amount}_{i,t-1} \\ & + \alpha_3 \textit{ Total Bids}_{it-1} + X_{it}\beta_1 + \mu_i + v_{it} \qquad (1.2) \end{aligned}$$

[9] We have also experimented with a normalization of all variables except percentages by loan size. Results are similar to those reported in the paper and are available from the authors upon request.
[10] The results are qualitatively similar if we replace the percentage of the cumulative amount of bids made by experts with the percentage of cumulative number of bids made by experts.

Both equations (1.1) and (1.2) are estimated using five definitions of "expert". Also, in equation (1.2), the hour of day fixed effect and weekend fixed effect are included but not reported. In addition to "following the crowd", investors' decisions could be driven by payoff externalities (Arieli, 2017). On *Renrendai.com*, investors take the opportunity cost that investing in a listing that may fail to complete. Although the contribution is fully refunded if the listing fails, investors still waste their time and potential opportunity. Hence, investment into nearly completed listings has several advantages. This fact may further boost the completion speed and enhance the impacts of expert imitation and herding.

To capture the payoff externalities, we interact the *Lag Percentage Need*, the percentage remains unfunded to measure the opportunity cost, with the *Lag Total Bid Amount.* The augmented model is shown below:

$$\begin{aligned} \textit{Hour Bid Amount}_{it} &= \alpha_1 \textit{Expert Amount Percent}_{i,t-1} + \alpha_2 \textit{Total Bid Amount}_{i,t-1} \\ &+ \alpha_3 \textit{Total Bids}_{i,t-1} + X_{it}\beta_1 + Z_i\beta_2 \\ &+ \alpha_4 \textit{Total Bid Amount}_{it-1} \times \textit{Lag Percentage Need} + \varepsilon_{it} + e_{it} \quad (1.3) \end{aligned}$$

1.5 Results

Table 1.2 presents the results for the presence of sequential correlation using all five expert proxies that we described above. These regressions control for loan- and borrower-specific characteristics. Next, Table 1.3 presents the results for expert imitation after we introduce both the hour of day and the listing fixed effects into the model. Table 1.4 presents the results for expert imitation among different categories of investors after we categorize investors into different groups based on experience.

1.5.1 Sequential correlation

Using the expert identifiers from both count measures and centrality measures, we examine for sequential correlation in Table 1.2. We include *Expert Amount Percent*, the percentage of the cumulative amount which is attributed to expert; *Lag Total Bid Amount* refers to the funding amount that the listing receives. Columns 1-2 show the results based on the expert definition stemming from the count measure by amount, or by the number of bids. The last three columns report the results based on expert lists stemming from degree centrality by weight, the number of ties, and the balanced degree centrality measure.

To detect expert imitation, we inspect the coefficient associated with *Expert Amount Percent.* The positive significant *Lag Expert Amount Percent* coefficient suggests that the expert decisions have a significant influence on investors in the *Renrendai* community: A listing receiving more past contributions from experts does attract more subsequent funding. Precisely, if *Lag Expert Amount Percent* increases by 50 percentage points, we would expect to observe an approximately 6 to 8 percent increase in the funding that a listing receives in the next hour.[11] In other words, when investors explore the historical biddings, if there are more amount attributes to experts instead of average non-experts, they would provide more contributions to this listing. Overall, the more experts who appear on the historical bidding record, the more appealing the listing becomes to the observant investors.

Apart from expert imitation, we also observe evidence of herding. The coefficient of *Lag Total Bid Amount* is statistically significant and positive as well, which suggests that the more lenders contribute, the more investors would follow. A similar finding was reported by Zhang et al. (2012). Furthermore, we find that *Lag Total Bids* takes a positive coefficient in all the columns, suggesting that the earlier the bids appear in a listing, the more future investors will provide funding. This finding also supports herding behaviour, as investors, while making decisions, observe both the bids list and the amount of all bids.

When we turn to the remaining independent variables in the model, we firstly find that the *Automatic Bidding Percent* negatively affects the hourly bid amount, which suggests that the automatic bidding system discourages the investment intent on listings. This is interesting, as the primary function of the automatic bidding service is to ease investors' decision-making problem and therefore, increase the overall amount invested in a listing. *Lag Percentage Needed* has a positive effect, which indicates that when a listing approaches completion, investors' interest in this listing declines. As a result, it takes a slightly longer time to fill the listing. We find that *Amount Requested* has a positive effect on the total bid, which indicates that a listing that asks for a larger amount can attract the attention of investors. *Log (number of) Bidders* has a positive impact on the amount of the bid. This is meaningful because as the number of bidders increases, so does the amount bid on a listing.

Our results show that several borrower and listing characteristics also affect the lenders' decision. *Interest Rate* takes a positive coefficient, reflecting that investors are attracted by high returns. *Log (Monthly) Income* has a positive coefficient, suggesting that investors prefer to

[11] We also run a subsample test based on the borrower rating of the loans. The results are reported in the Table TA1.8. We divided the entire sample into three subsamples (High, Mid, Low) based on the borrower ratings of the loan (High stands for loans with Credit Level = 1 or 2; Mid stands for loans with Credit Level = 3 or 4 or 5; Low stands for loans with Credit Level = 6 or 7). We found that, the herding evidence exists in all loan rankings. However, the expert imitation exists in high and low ranking loans. However, the expert imitation is rarely detected among mid-ranking loans.

fund applicants with higher incomes, as high-income applicants can be considered less risky. *Debt-to-Income Ratio* takes a negative coefficient, suggesting that investors tend to avoid borrowers with high debt levels. *Credit Risky* has a negative coefficient in all five columns. To avoid risk, investors are certainly filling loan requests of applicants with better credit scores. *Maturity* takes a negative coefficient; investors on *Renrendai* seem to prefer short-term loans over loans that mature further into the future. The negative coefficient associated with the interaction between *Lag Total Bid Amount* and *Lag Percentage Needed* suggests that as a listing approaches completion, investors will reduce their funding to that particular list.[12] Given the speed of the action on Renrendai.com, investors must be quick in identifying opportunities for new listings are posted as the older ones fill over the course of the day. Overall, the findings inTable 1.2 provide evidence of expert imitation and herding, and the role of the remaining variables in the model is similar to results in earlier work.

1.5.2 Listing heterogeneity and payoff externalities

Having confirmed the sequential correlation for expert variation, we introduce listing fixed effects to control for listing heterogeneity. We include listing fixed effects to check for whether the expert imitation and herding are overestimated, as the positive sequential correlation result could be driven by the unobserved heterogeneity across listings and payoff externalities among lenders. Thus, all listing- and borrower-specific characteristics are dropped from our econometric specifications.

When we inspect Table 1.3 we find that *Lag Expert Amount Percent* still takes a highly significant positive coefficient, which suggests the presence of expert imitation on *Renrendai.com*. *Lag Total Bid Amount* is statistically significant and positive. This suggests herding behaviour in the community. These findings confirm that the expert, as well as the herding, exist in the P2P market. Furthermore, herding seems to be overestimated in the main result. *Lag Total Bids* has a positive effect on the investors' decisions, which is consistent with the earlier results (Zhang et al., 2012). The coefficient of *Log (Bidders)* is significantly positive, which suggests that the number of lenders on the market increases the amount that a listing receives. Finally, the interaction term *Lag Total Bid Amount* × *Lag Percentage Need* does not take a significant coefficient. This finding is meaningful from two perspectives. First, the impact of herding would not significantly change over the entire fundraising progress. The earlier (or later) bidding in the entire bidding cycle time would not affect the herding evidence

[12] We observe a negative coefficient for the interaction term in Table 1.4, as well.

The insignificant interaction term indicates that, the positive evidence of herding is not driven by payoff externalities. Second, the insignificant payoff externalities is sensible to the particular settings of the market. Differs from crowd funding platform, the P2P lending platform is rather active, a loan would be fully funded in about 5 hours. Therefore, the loans posted earlier would be buried by the new-loans, therefore the speed of funding would be even slower than the beginning. This phenomenon might be raised by the specific market model and setting of Renrendai bidding system. Overall, the findings in Table 1.3 corroborate the expert imitation evidence and herding evidence in our main results.

1.5.3 Extensions

Our analysis is further extended by the categorization of investors based on recent experience. Within every four-month rolling window, we identify *Active Investor* if she invested during the first three months. However, an investor can enter the window in the fourth month; in this case, she is defined as *New Investor*. We split investors based on experience because the expert imitation comes from observational learning during the learning interval. Without sufficient learning, it is rarely possible to acquire expert acknowledge. Furthermore, although some *New Investors* might have participated in the previous windows, because “expert” is continually updated, the lack of earlier activity in a window indicates that they are less likely to observe and learn during the current rolling window. Active investors are further split into experts and non-experts based on the balanced degree definition of experts. Active investors are not always considered experts. Active non-experts have a level of investment that is lower in frequency and quantity as compared to those identified as experts. Hence, Model (1) is estimated for all four groups and the results are reported in Table 1.4.

When we examine the effect of expert imitation on active investors (Column 1), we find that *Active Investors* are likely to imitate the decisions attributed to experts. Meanwhile, the coefficient of *Lag Total Bid Amount* suggests that these *Active Investors* also herd. Interestingly, when we compare these results to *New Investors* (Column 2 of Table 1.4), we do not detect the expert imitation while herding is still present: The coefficient of *Lag Total Bid Amount* is positive and significant for this group suggesting that the new investors are inclined to follow the collective investors’ decisions. This is perhaps because the new investors have not observed enough listings to identify experts and, thus, they prefer to simply follow the crowd.

When we examine the behaviour of both active experts and active non-experts as reported in Columns 3 and 4, we find that the latter are positively affected by other experts’ decisions, while the evidence for the former is not conclusive (negative and weakly significant). This phenomenon can be explained by the difference in perception between both experts and non-experts. When they observe historical biddings, non-experts might be geared towards using information extracted from experts' bids as an aid to their investment decisions, whereas experts do not pay attention to other experts. However, both types of investors are positively affected by the *Lag Total Bid Amount*, which suggests that both experts and non-experts herd, whereas non-experts are more likely to follow the crowd decisions. As we explained in the introduction of this chapter, those experts we defined, they do not really show more "expertise" or "professions". They are influential investors as they are much more active than the general investors. The effect of "bidding the loans which has already attract a lot of money" ("wait and bid") strategy is also controlled in the estimation using the variable named "Lag Percentage Needed". The expert imitation could be simplified as this situation: if there are two loans listings equipped with almost the same loan and borrower features, and both of them currently have received the same amount of funding, the investors are more likely to bid to the loan which attracts more biddings from experts. In all the estimations, expert imitation is detected when both herding and "wait and bid" terms are included.

1.6 Conclusion

During the past decade, online peer-to-peer lending platforms have benefited both investors who sought better returns for their hard-earned savings and credit-constrained borrowers who had difficulty obtaining loans by resorting to traditional means. However, P2P lending platforms are still in development; in particular, most investors are not adequately equipped with the expert knowledge to cope with the risks associated with lending on these platforms. Earlier literature has shown that, under uncertainty, investors herd. However, given that investors can observe historical data about the lending behaviour of all other investors, it would be possible to single out investors who have expert information on listings posted on the platform. When such individuals are identified through observation, rather than blindly following the crowd, i.e. herd, investors may prefer to follow expert behaviour and mimic their lending pattern.

Our research focuses on data extracted from *Renrendai.com* and shows, for the first time, that observational learning takes place in P2P markets and that naïve investors learn through observation and imitate market leaders' lending behaviour. Using sequences of rolling windows over historical bidding data, we empirically identify some investors as experts using count methods and network centrality measures. Although these measures are different from each other, they successfully capture the top investors in the P2P community and provide similar results. Introducing these measures into an empirical framework similar to models that researchers have used to examine the presence of herding behaviour, we show that experts' lending behaviour significantly and positively affects the lending behaviour of the remaining P2P investors in the community. In other words, we provide evidence that investors observe and learn from experts and act in line with expert behaviour. Finally, we show that experts do not follow other experts in the community, but they have the tendency to herd. This is perhaps because herding behaviour is ultimately subconsciously inherent in all living beings. We believe that further research along these lines would be beneficial.

Tables

Table 1.1: Descriptive Statistics for Loan Characteristics

	Mean	Std	p25	p50	p75
	(1)	(2)	(3)	(4)	(5)
Loan Amount	49,142.76	43,465.87	15,000.00	41,100.00	73,700.00
Interest Rate (%)	12.29	2.61	10.80	12.00	13.00
Maturity (Months)	21.79	12.29	12.00	20.00	36.00
Credit Risky (1=yes)	0.22	0.41	0.00	0.00	0.00
Debt-to-Income Ratio	0.28	0.36	0.11	0.19	0.35
Monthly Income	4.37	1.28	3.00	4.00	5.00
High Education	0.67	0.47	0.00	1.00	1.00
Time on Market	4.22	17.12	0.00	0.00	0.00
Obs.	111,234				

Note: This table shows the mean (1), standard deviation (2), and quartiles (3)-(5) of the following variables. *Loan Amount* represents the total amount of the loan received. *Interest Rate (%)* represents the annual percentage rate on the loan. *Maturity* represents the current loan duration in months. *Credit Risky (1=yes)* means that the listing's credit grade is E or below, i.e. E, F, and HR, else=0. *Debt-to-Income Ratio* represents the ratio of the borrower's monthly debt divided by gross income before the borrower applies for loans. *Monthly Income* represents the monthly income (measured by 1000) for every borrower. *High Education* represents that the borrower holds a certificate that is above or equal to college level. *Time on Market* represents the time duration term that a listing is posted on the platform before it is full.

Table 1.2 Descriptive Statistics for bidding-hour level sample

	Mean	Std	p25	p50	p75
	(1)	(2)	(3)	(4)	(5)
Hourly Total Bids	6.44	19.03	0.00	0.00	5.00
Hourly Total Experts Bids	1.88	4.98	0.00	0.00	1.00
Hourly Total Non-Experts Bids	4.56	15.54	0.00	0.00	3.00
Hourly Bid Amount	9,368.00	23,609.70	0.00	0.00	3,500.00
Hourly Experts Amount	3,511.97	11,615.26	0.00	0.00	400.00
Hourly Non-Experts Amount	5,856.03	16,213.16	0.00	0.00	1,750.00
Hourly Experts Amount Percent	0.39	0.32	0.10	0.32	0.64
Log Bidders	5.06	2.03	3.64	4.88	5.77
Percent Needed	63.46	37.60	31.67	81.67	95.00
Obs.	432,882				

Note: This table shows the mean (1), standard deviation (2), and quartiles (3)-(5) of the following variables. *Hourly Total Bids* represents the hourly total number of bids from lenders for a loan request. *Hourly Total Experts Bids* represents the hourly total number of bids from experts for a loan request. *Hourly Total Non-Experts Bids* represents the hourly total number of bids from non-experts for a loan request. *Hourly Bid Amount* represents the hourly bid amount a listing receives. *Hourly Experts Amount* represents the hourly bid amount a listing receives from experts. *Hourly Non-Experts Amount* represents the hourly bid amount a listing receives from non-experts. *Hourly Experts Amount Percent* represents the percentage of the bid amount a listing receives attributed to experts. *Log Bidders* represents the logarithm of number of bidders. *Percent Needed (%)* represents the percentage of the amount requested that is left unfunded. In this table, the measurement of expert identification is built on the balanced degree centrality which considers both the weight and number of the connections.

Table 1.2: Sequential Correlation and Expert Imitation

	Count Amount	Count Bids	Degree Amount	Degree Bids	Balanced Degree
	(1)	(2)	(3)	(4)	(5)
Lag Expert Amount Percent	0.122***	0.133***	0.127***	0.169***	0.152***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Lag Total Bid Amount	0.313***	0.316***	0.313***	0.318***	0.318***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Lag Total Bids	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag Percentage Needed (%)	0.009***	0.009***	0.009***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag Percent Automatic Bidding	-0.801***	-0.792***	-0.795***	-0.824***	-0.812***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Amount Requested	0.163***	0.162***	0.162***	0.158***	0.152***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
Interest Rate (%)	0.013***	0.012***	0.013***	0.013***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Maturity	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Monthly Income	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
High Education	0.012**	0.014**	0.015***	0.011**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Credit Risky	-0.105***	-0.102***	-0.102***	-0.103***	-0.105***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Debt-to-Income Ratio	-0.004	-0.001	-0.002	0.002	-0.012
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
Log Bidders	1.231***	1.231***	1.232***	1.231***	1.230***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Lag Total Amount × Lag Percentage Needed (%)	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	432,882	432,882	432,882	432,882	432,882
R2	0.849	0.849	0.848	0.849	0.849

Note: This table shows the sequential correlation of the following variables based on (1) Count Amount Method, (2) Count Bids Method, (3) Degree Amount Method, (4) Degree Bids Method, and (5) Balanced Degree Method. The dependent variable of all five clusters is *Log Hour Bid Amount*. *Lag Expert Amount Percent* represents the percentage of the total amount of the loan received from experts at time t-1. *Lag Total Bid Amount* shows the total amount of funding from collective investors at t-1. *Lag Total Bids* represents the total number of bids at *t-1*. *Lag Percentage Needed (%)* represents the percentage of the amount requested that is unfunded at *t-1*. *Amount Requested* represents the requested loan amount. *Interest Rate (%)*

represents the annual interest rate of the loan. *Maturity* represents the loan duration in months. *Monthly Income* represents the monthly income of the particular borrower. *High Education (1=yes)* represents whether the borrower holds a high education certificate. *Credit Risky (1=yes)* represents the listing's credit grade, i.e., E, F, or HR, else=0. *Debt-to-Income Ratio* represents the ratio of the borrower's monthly debt divided by gross income before they apply for loans. *Log Bidders* represents the logarithm of bidder numbers. *Lag Percent Automatic Bidding* shows the percentage of automatic bidding at *t-1*. The *Hour of Day* dummy variables are included but not reported.

*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Robust standard errors are presented in parentheses.

Table 1.3: Fixed Effect and Expert Imitation

	Count Amount	Count Bids	Degree Amount	Degree Bids	Balanced Degree
	(1)	(2)	(3)	(4)	(5)
Lag Expert Amount Percent	0.121***	0.172***	0.137***	0.193***	0.166***
	(0.017)	(0.018)	(0.017)	(0.019)	(0.018)
Lag Total Bid Amount	0.145***	0.152***	0.145***	0.153***	0.145***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Lag Total Bids	0.004***	0.005***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag Percentage Needed (%)	0.001	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag Percent Automatic Bidding	-0.547***	-0.541***	-0.536***	-0.556***	-0.554***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Lag Total Amount × Lag Percentage Needed (%)	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Bidders	1.267***	1.268***	1.269***	1.267***	1.267***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Obs.	432,882	432,882	432,882	432,882	432,882
R2 (within)	0.709	0.709	0.709	0.709	0.709

Note: This table shows the Fixed Effect Model results of the following: Count Amount Method, (2) Count Bids Method, (3) Degree Amount Method, (4) Degree Bids Method, and (5) Balanced Degree Method. The dependent variable of all five clusters is *Log Hour Bid Amount*. *Lag Expert Amount Percent* represents the percentage of the total amount of the loan received from experts at time *t-1*. *Lag Total Bid Amount* shows the total amount of funding from collective investors at *t-1*. *Lag Total Bids* represents the total number of bids from lenders at *t-1*. *Lag Percentage Needed (%)* represents the percentage of the amount requested that is left unfunded at *t-1*. *Log Bidders* represents the logarithm of bidder numbers. *Lag Percent Automatic Bidding* shows the percentage of automatic bidding at t-1. The *Hour of Day* dummy variables are included but not reported.

*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Robust standard errors are presented in parentheses.

Table 1.4: Active vs New Investors

	Active	New	Active Experts	Active Non-experts
	(1)	(2)	(3)	(4)
Lag Expert Amount Percent	0.108***	-0.002	-0.028*	0.193***
	(0.006)	(0.017)	(0.016)	(0.017)
Lag Total Bid Amount	0.337***	0.281***	0.323***	0.429***
	(0.013)	(0.011)	(0.015)	(0.016)
Lag Total Bids	0.011***	0.010***	0.010***	0.011***
	(0.002)	(0.001)	(0.002)	(0.002)
Lag Percentage Needed (%)	0.011***	0.014***	0.014***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Lag Percent Automatic Bidding	-0.764***	-0.531***	-0.613***	-0.687***
	(0.018)	(0.014)	(0.016)	(0.016)
Amount Requested	0.118***	0.050***	0.080***	0.022***
	(0.007)	(0.007)	(0.007)	(0.008)
Interest Rate (%)	0.015***	0.012***	0.019***	0.017***
	(0.000)	(0.001)	(0.001)	(0.001)
Maturity	-0.018***	-0.012***	-0.017***	-0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
Credit Risky	-0.077***	-0.119***	-0.038***	-0.102***
	(0.008)	(0.009)	(0.009)	(0.011)
Debt-to-Income Ratio	0.016	0.019*	0.021*	0.029**
	(0.011)	(0.011)	(0.011)	(0.011)
Monthly Income	0.012***	0.007	0.011***	0.015***
	(0.003)	(0.004)	(0.004)	(0.005)
High Education	0.017***	0.001	0.022***	0.015**
	(0.006)	(0.007)	(0.007)	(0.008)
Log Bidders	1.271***	1.424***	1.371***	1.332***
	-0.003	(0.003)	(0.003)	-0.003
Lag Total Amount × Lag Percentage Needed (%)	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	354,252	246,491	255,174	235,411
R2	0.855	0.867	0.863	0.857

Note: This table shows the OLS result with *Log Hour Bid Amount* as the dependent variable. The investor is defined as *Active* if she bid during the first three months of a four-month rolling window. Otherwise, the investor is defined as *New* if she entered the window only in the fourth month. *Expert* is defined based on the balanced degree definition. *Lag Expert Amount Percent* represents the percentage of the total amount of the loan received from *Expert* at time t-1. *Lag Total Bid Amount* shows the total amount of funding from collective investors at t-1. *Lag Total Bids* represents the total number of bids at *t-1*. *Lag Percentage Needed (%)* represents the percentage of the amount requested that is unfunded at *t-1*. *Amount Requested* represents the requested loan amount. *Interest Rate (%)* represents the annual interest rate of the loan.

Maturity represents the loan duration in months. *Monthly Income* represents the monthly income of the particular borrower. *High Education (1=yes)* represents whether the borrower holds a high education certificate. *Credit Risky (1=yes)* represents that the listing's credit grade is E, F, or HR, else=0. *Debt-to-Income Ratio* represents the ratio of the borrower's monthly debt divided by gross income before they apply for loans. *Log Bidders* represents the logarithm of bidder numbers. *Lag Percent Automatic Bidding* shows the percentage of automatic bidding at *t-1*. The *Hour of Day* dummy variables are included but not reported.

*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Robust standard errors are presented in parentheses.

Appendix

Appendix Table TA1.6 illustrates the definitions of variables appear in this analysis.

Appendix Table TA1.7 presents the descriptive statistics among Expert bidding vs. non-expert bidding.

Appendix Table TA1.8 reports the results of subsample test based on the borrower credit ratings.

Table TA1.5: Definitions of Variables

Variables	Definition
Hour Bid Amount	Hourly bid amount that a loan receives
Hour Total Bids	Hourly total number of bids that a loan receives
Hour Expert Bid Amount	Hourly bid amount that a loan receives from Experts
Hour Expert Bids	Hourly total number of bids that a loan receives from Experts
Expert Amount Percent	The percentage of the cumulative amount which is attributed to experts in a listing by the end of a certain hour.
Hour Percentage of Automatic bidding	The percentage of automatic biddings during a certain hour
Lag Percentage Needed	The percentage of amount requested that is left unfunded by the end of hour t-1
Debt to Income Ratio (%)	Ratio of borrower's debt divided by monthly income
Credit Risky	If = 1, the listing's credit grade is E or below, i.e. E or F or HR, else 0
Interest Rate (%)	Percentage rate of interest on the loan
Amount Requested (RMB)	Funding amount that a loan request
Maturity (Month)	Current loan duration (in months)

Table TA1.6: Overlapped Experts (intersection rate matrix)

Intersection Rate	Counting Bids	Degree Amount	Degree Bids	Balanced Degree
Count Amount	63.60%	90.90%	77.20%	90.90%
Count Bids		72.70%	95.40%	81.80%
Degree Amount			77.20%	90.90%
Degree Bids				86.40%

Note: This tables reports how many investors are tagged as "Experts" by both two measures in every column and row respectively.

Table TA1.7: Descriptive statistics among Expert bidding vs. non-expert bidding.

	Non-Expert			Expert		
	Mean	Std.	Obs	Mean	Std.	Obs
Interest Rate	11.7341	1.8584	2,283,281	11.9379	1.9126	1,171,675
Credit Level	2.0231	2.0547	2,283,281	2.0561	2.0681	1,171,675

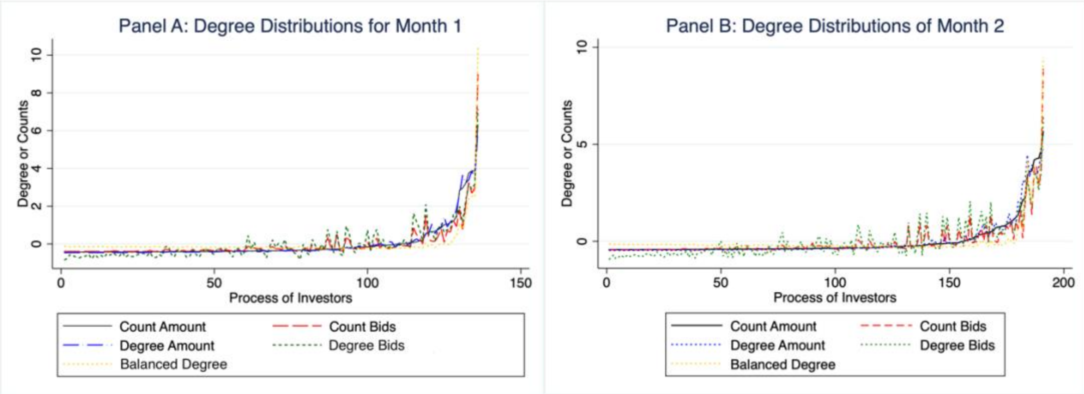
Note: This table reports the descriptive statistics for all biddings which funded by non-experts and experts, respectively. *Interest Rate* represents the interest rate measured by percentage points proposed by the borrower of the loan. Credit Level represents the rank of credit of the loans issued by the platform (In particular, 1 stands for AA, which is the highest level of credit.

Table TA1.8: Subsample Test based on the borrower credit ratings.

	(1)	(2)	(3)	(4)
	All	High	Mid	Low
Lag Expert Amount Percentage	0.142***	0.216***	0.013	0.122***
	(0.005)	(0.038)	(0.019)	(0.003)
Lag Total Bid Amount	0.311***	0.291***	0.476***	0.226***
	(0.012)	(0.058)	(0.021)	(0.024)
Lag Total Bids	0.011***	0.014**	0.010***	0.028***
	(0.002)	(0.007)	(0.002)	(0.003)
Lag Percentage Needed (%)	0.008***	0.013**	0.013***	0.009***
	(0.001)	(0.005)	(0.002)	(0.002)
Lag Percent Automatic Bidding	-0.812***	0.217	-0.998***	-0.707***
	(0.019)	(0.531)	(0.020)	(0.107)
Amount Requested	0.155***	-0.005	0.041***	0.187***
	(0.007)	(0.031)	(0.012)	(0.012)
Interest Rate (%)	0.013***	0.016***	0.065***	0.007***
	(0.000)	(0.005)	(0.002)	(0.000)
Maturity	-0.018***	-0.006***	-0.020***	-0.003***
	(0.000)	(0.002)	(0.001)	(0.000)
Credit Risky	-0.103***	0.000	0.000	-0.043***
	(0.008)	(0.000)	(0.000)	(0.015)
Debt-to-Income Ratio	0.007	0.452***	0.007	0.090***
	(0.011)	(0.129)	(0.014)	(0.013)
Monthly Income	0.009***	0.033	0.004	-0.001
	(0.003)	(0.022)	(0.008)	(0.002)
High Education	0.011*	0.027	0.011	-0.019***
	-0.006	-0.037	-0.012	-0.004
Log (Bidders)	1.230***	1.713***	1.149***	1.422***
	-0.003	-0.018	-0.003	-0.003
Lag Total Amount * Lag Percentage Needed (%)	-0.001***	-0.002***	-0.001***	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
Obs.	430,399	8,300	149,302	272,797
R2	0.849	0.832	0.744	0.864

Note: This table shows sequential correlation of following variables based on Balanced Degree Method. The dependent variables and independent variables are consistent with the settings in Table 1.3. The entire sample is divided into three subsamples (High, Mid, Low) based on the borrower ratings of the loan (High stands for loans with Credit Level = 1 or 2; Mid stands for loans with Credit Level = 3 or 4 or 5; Low stands for loans with Credit Level = 6 or 7). *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Robust standard errors are presented in parentheses.

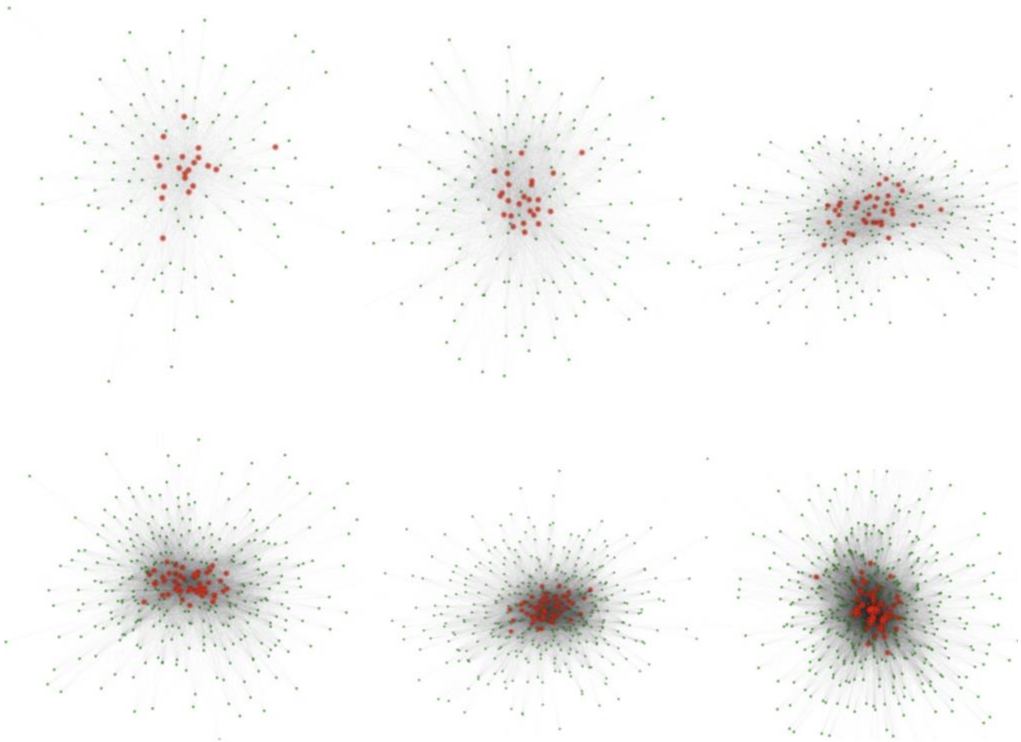
Figure FA1.1: Degree Distribution of 5 methods



Note: Panel A contains the degree distributions for a three-months subsample starts from the first month of the entire sample period (October 2010, we define it as Month 1). Panel B represents the degree distributions for the Month 2.

In Panel A we generate a ranking based on the total bid amount of 136 investors. We re-code the *lender ID* so the investor who has the smallest amount is the No.1, the biggest amount belongs to No. 136. We also introduce the number of bids into the distribution based on same *lender ID*. Then, we consider the *Degree Amount, Degree Bids* and *Balanced Degree.* It is clear 5 rankings are not always the same, but it would show the similar tendency. If the two rankings are the same, the two distribution lines should be totally matched. In Panel B, we do the same procedure on Month 2, it is observable that rankings in Month 2 are different from Month 1.

Figure FA1.2: Examples of investor community networks.



Note: This figure shows a toy example of the network structure exists in the P2P investor community. In particular, these figures represent the networks structured by the investment behaviour on monthly basis from October 2010 to March 2011. The revolving network structure indicates the influence patterns in the investor community is also in changing.

Chapter 2: Asset price dynamics in a P2P market: the role of COVID-19 news

2.1 Introduction

Information arrival has been broadly recognized as one of the most profound factors driving asset price determination. Previous studies suggest that asset prices should adjust to public information such as monetary announcements (Galí and Gambetti, 2015), bank announcements (Ongena et al., 2014). Rare disasters could also contribute to asset price drifts (Jha et al., 2021). Recent studies explore the effect of the COVID-19 (C19) crisis on asset holdings, focusing on equity (Ozik et al., 2021) and bank loans (Li and Strahan, 2021). There is also evidence that C19 news affects other areas of finance, such as corporate bonds (Ding et al., 2021) and BigTech innovations (Bao and Huang, 2021). Yet, evidence on how individual peer-to-peer (P2P) investors react to official C19 announcements is still untouched. This paper fills this gap by examining the extent to which European P2P investors price their assets originated from Spain differently following official C19 announcements made by the Spanish government.

Different from investors in traditional financial markets, P2P investors benefit from a cost-efficient transaction process and information transparency. The P2P lending market is composed of unprofessional investors and borrowers facing reduced credit access from traditional banking (Zhang and Liu, 2012). The transaction costs in P2P markets are rather low as investors and borrowers are matched without intermediary (Lee and Lee, 2011). Similarly, the P2P loan is equipped with both loan information and personal characteristics of the borrower who create this loan, which is valuable in investment decision-making progress (Zhang et al., 2012). P2P lending market furnishes unique environment for investigating our research questions.

We focus on Spain, one of the countries worst hit by the C19 pandemic. The outbreak of C19 in Spain has led to an unprecedented crisis in Spanish economic and finance sectors (Boscá et al., 2020; Pedauga et al., 2020 and Foremny et al., 2020). Since the first case confirmed in early February 2020, Spain has become the second C19 epicenter in Europe.[13] The Spanish stock market returns are significantly affected by the C19 pandemic (Ahmar and Del Val, 2020; Gherghina et al., 2020 and Phan et al., 2020). Also, the C19 outbreak imperils the credit availability from banking system in Spain (Nigmonov and Shams, 2021). The unexpected development of C19 in Spain provides an unfortunate but valuable opportunity for this study. Consequently, this study focuses on the effects of Spanish governmental C19 announcement on Spain-originated P2P loans.

[13] Spain has one of the highest burdens of C19 infections in the first a few months during the pandemic (Guirao, 2020).

To pursue the investigation, we employ loan transaction data from Bondora secondary market, one of the leading P2P lending platforms in continental European. This alternative banking resource facilitates funding to individuals located in Spain, Estonia, Finland and Slovakia, and attracts investors from pan-European countries.[14] The platform operates both primary and secondary markets. The primary loan service allows lenders to directly invest in loans created by borrowers. Then, those loans would be moved to secondary market in which loan holders are allowed to list their notes (shares of loans) originated from the primary marketplace. The transaction record and repayment history of the P2P loans are visible to investors; both sellers and buyers could use transparent information to help them make decisions. Our data include 75,084 loan-week observations pertaining to 12,012 loans and 623,219 over the period 1 February 2020 to 31 May 2020.[15] We then extract daily confirmed case and death counts from Spanish Health Ministry archives.[16]

We first illustrate how C19 announcements affect the notes' pricing dynamics. Our data suggest that sellers ask lower price and list fewer notes in response to the Spain C19-case updates. For instance, a 10,000 increase in Spain weekly new-confirmed cases leads to a 2.4 percentage points drop in note prices. Considering the average asset price are approximately 11.2 before pandemic, the economic significance is relatively large. Buyers are more likely to agree the asked price, as a 10,000 increase in Spain cases is associated to 2.2 percent points increase in the share of success transaction. The regional C19 updates are moderately associated to investor decisions: a 10,000 increase in new cases in a region is associated with a modest 0.7 percentage points decrease in price.[17] This suggests that, compared to the country updates, investor attention to regional statistics is less efficient. That is, investors tend to rely more on Spain-wide statistics compared to regional updates when pricing their loan holdings.[18]

We further explore the investor inattention to the regional C19 updates. We posit this inattention might be explained by the insignificant media attention on region-level C19 topics. We obtain Google trends indices, as well as online newspaper articles among European

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[14] *Bondora* investors are required to hold EU citizenships. Some non-EU countries are also approved by *Bondora*, such as Iceland, Liechtenstein, Norway, Switzerland, United Kingdom.

[15] This period starts from the 1 Feb 2020, at which the first case in Spain was confirmed. And due to EU data protection intervention, Bondora stopped depositing borrowers' region-specific information from June 2020. Therefore we only include the transaction records before this policy change occurred.

[16] C19 case counts have been used in several works to probe the C19 impact on stock market (e.g., Engelhardt et al., 2021 and Bretscher et al.,2020). The trajectory of C19 infections could be related to the asset pricing movements during pandemic (e.g., Alfaro et al, 2020).

[17] Recent studies such as Dey et al (2020) also find local C19 spreads is associated to S&P 500 index movements.

[18] Besides the direct information proxy, we utilize a measurement of governmental lockdown restrictions. The results are quantitively similar.

countries on C19 topics for Spain and its regions.[19] We then include both the national and regional C19 media attention indices in our models. Including the effects of C19 announcements, our estimates suggest that regional C19 media attention is insignificant to asset pricing dynamics. In contrast, media attention on country-specific C19 topics is significantly related to investors' decision-making. These findings indicate that regional C19 information gains insufficient online media attention: investors are more likely to assess country-wide news rather than searching detailed updates; also, macro level C19 information is more likely to be propagated, whereas the media coverage of C19 topics on region-level is not sufficient. Hence, the investors might be inattentive to the region-specific C19 information.

This paper builds on literature about the connect between asset pricing and public information.[20] Previous studies focus on the role of governmental announcement on stock market (Bernile et al, 2016; Lillo et al, 2015), futures market (Kuttner, 2001), hedge funds (Cao et al, 2013) and currency exchange market (Ho et al., 2017). P2P lending provides a marketplace in which investors equipped no professional acknowledge could seek profits from unsecured loan fundraising. Indeed, this study differs in turning attention to how governmental announcement is associated to asset pricing movements in a P2P secondary market. The C19 announcements are responsible to the subsequent asset pricing movements since the C19 outbreak. Regarding the P2P secondary market is consisted by individual investors, the estimations on asset mispricing would be beneficial to facilitate decision-making of both sellers and lenders.

This paper also adds to the literature shedding light on the role of investor inattention. In general, previous literature suggests that, compared to macro wide information, micro news might be overlooked since investors have only limited attention (see e.g., Peng and Xiong, 2006; Andrei and Hasler, 2015; Curtis et al, 2014; Chen, 2017). We link the investor inattention to micro news to the media attention and supply of information. Observing macro and micro news play different roles in asset pricing drifts, we then document the inattention to micro news might be associated to the insignificant media attention to region-specific C19 topics. Also, compared to nation-level updates, region level message is harder to access due to the deficient information supply.

[19] Similarly, Ramelli and Wagner (2020) use Google Trends on specific firms to proxy the investor attention.
[20] For example, Assenmacher and Gerlach, (2008); Bourdeau-Brien and Kryzanowski, (2017); Boudoukh et al. (2019) and Crane et al. (2019).

Last, this paper relates to the evolving research on the impact of C19 on FinTech industry. Recent studies have investigated the effect of C19 crisis on financial market.[21] Some papers focus the impacts of C19 crisis on banking markets (such as Colak and Oztekin, 2020; Hasan et al., 2020) and FinTech companies (e.g., Bao and Huang, 2021). P2P lending is an integral sector of FinTech lending, and it plays critical roles in alternative credit market (Roule et al., 2016). We stress the effects of C19 announcement on a peer-to-peer marketplace of FinTech innovation. Indeed, this study contributes to literature by estimating the negative effects of C19 crisis on individual investors in a P2P secondary market. Also, this study exploits the connect between lockdown restrictions and P2P investor decisions.

The rest of this paper is organised as follows. Section 2 provides an overview of Bondora platform. Section 3 presents the literature review and hypothesis development. Section 4 presents the description of the data. Section 5 presents the empirical specifications. Section 6 discusses the results and extensions. Finally, Section 7 conclude this paper.

2.2 Economic background and hypotheses development

2.2.1 Information arrival and asset pricing

A substantial literature has investigated the role of information arrival in asset pricing dynamics (e.g. Kalev et al, 2004; Galí and Gambetti, 2015 and Crego, 2020). Empirical evidence has found that investors tend to change their asset price according to the updates of new information (e.g. Melvin and Yin, 2000; Ho et al., 2018; Wu et al, 2019). For instance, Mitchell and Mulherin (1994) find that the Dow Jones announcement and stock market activities such as trading volume and market returns are directly associated. Chan (2003) documents that public newspaper headlines might be responsible for subsequent stock price changes, and that strong drifts could be observed after the arrival of bad news. Using online newspaper resource to proxy the information flows, Shi et al. (2016) suggest that firm-specific news is important to understand expected stock returns.

Besides the firm news and financial market messages, information released by public sectors and governmental authorities may also play a profound role in the asset pricing dynamics (Henry, 2000; Ramiah et al., 2013) For example, Pearce and Roley (1984) document the stock markets response to economic announcements related to inflation, money supply and real economic activity. They also find that monetary policy movements also drive the stock prices.

[21] See Ding, Levine, Lin and Xie, (2020) and Andries, Ongena and Sprincean, (2020) for comprehensive studies of the C19 impact.

In developing countries like Turkey, GDP reports and industrial production announcements play a significant role in explaining the movements of stock returns (Kutan and Aksoy, 2004). Brzeszczynski and Kutan (2015) find that central bank communications in Poland relieve the uncertainty in financial markets and increase the foreign exchange market trading volume. Moreover, Hong et al. (2021) document that investors would adjust their lending decisions based on the information content in forward guidance statements.

The mechanism underlying the C19 information effect on the financial market response has been also explored by several prior studies. Yarovaya et al. (2022) construct a review on the C19 information transmission channels by catalysts of contagion and “black swan” event; media attention; spillovers effect in financial markets and contagion through macroeconomic fundamentals. First, the C19 effect could trigger the movements in asset pricing dynamics by depress the investor expectations. For instance, Gormsen and Koijen (2020) investigates how COVID-19 affect investors’ expectations using aggregate stock and dividend futures from the US, Japan and the EU. Second, the C19 effect could affect the investor risk perceptions (e.g., Bai et al., 2020). For instance, the COVID-19 shock risk perceptions for particular industries such as fossil-fuel industrial sectors (Szczygielski et al., 2021). Third, Google search volume and social network transmission also play profound implications in the investor COVID-19 fears (Lyócsa et al., 2020). Smales (2021) suggests that the Google search volume proxies the attention of retail investors, and the investor attention negatively influences the stock returns among global markets in the pandemic period.

In light of this literature, we suggest that C19-related information released by the Spanish government may be associated with a downward movement in asset pricing for the following reasons. First, there is evidence that stock market investors tend to reduce the prices of their assets in response to the C19 pandemic. For instance, He et al. (2020) investigate the effect of the C19 pandemic on the Chinese stock market throughout an event study strategy. Their results suggest that several industrial sectors such as mining, environmental technology and transportation were adversely impacted by the C19 pandemic.

Second, the official announcement related to infections and deaths have been employed to directly proxy for the C19 intensity (Ding et al., 2021). Recent studies suggest that official announcements about C19 infection numbers exhibit negative effects on asset pricing dynamics (Alfaro et al., 2020). For instance, Al-Awadhi et al. (2020) posit the China C19 cases have a negative effect on stock returns across companies included in the Hang Seng Index (HSI) and Shang Hai Exchange (SSE) Index[22]. Albulescu (2020) suggests that the unexpected S&P 500 stock price drops in March 2020 are associated to the ongoing C19 confirmed cases. Similarly, Baig et al. (2021) indicate the increasing C19 cases and deaths are related to the expanding market liquidity and volatility in US stock market.

Third, P2P investors are observed to make use of public information provided by the platform. (Lee and Lee, 2021). The public information comes from various sources. For instance, the P2P platforms provide borrower-specific information such as employment status, residence location and property ownership, which are usually taken into the decision-making (Caglayan et al., 2021b). Besides the inner P2P market information, investors also make use of the information publicly accessible in the outer world (e.g., Zhang et al., 2017). Specifically, official announcements such as monetary policy changes (Adrian and Shin, 2009; Huang et al., 2021) and changes in the P2P regulation policy (Huang, 2018) have profound implications in the decision making. Empirical evidence suggests that public official C19 announcement are associated with asset drops in financial markets (Papadamou et al., 2021). In line with this literature, we propose the following hypothesis:

H1: Investors reduce their current asset price in response to the C19 announcement updates.

2.2.2 Country-level news vs. region-level news

The official coronavirus announcements contain macro level and micro level messages: in Spain, both nation-wide confirmed cases/deaths and region-specific confirmed cases/deaths are updated on a daily basis. Substantial empirical studies have compared investors' reactions to macroeconomic news and micro-level information (e.g. Gilbert 2011; Hirshleifer et al., 2009, 2011). Peng and Xiong (2002) suggest that macro-level news crowd out micro-specific news, which leads to less efficient processing of firm earning announcements. By contrast, Hirshleifer and Sheng (2021) document a complementary relation between macro news and micro news as the macro-wide information enhances the investors' sensitivity to micro level news. The Spanish governmental C19 announcement constructs an information environment in which macro and micro news are updated categorically. Although the nation-wide statistics is aggerated from the localized infection numbers, in the real information environment, there are two separately announced information flows. These two numbers are separated by the governmental announcement. This is essential as it provides the opportunity to chase the

[22] Hang Seng Index (HSI) is a free-float-adjusted market-capitalization-weighted stock-market index in Hong Kong Stock Exchange. The SSE Index is a stock market index of all stocks that are traded at the Shanghai Stock Exchange.

categorical response to different level of information flows.[23] Therefore, we do not need to separate them by ourselves, they are created and announced separately.

Bondora's secondary market provide rich informational transparency for investors to facilitate their decisions (Gavurova et al., 2018). All loans listings posted in the secondary market are equipped with loan characteristics, such as loan amount, maturity, credit rating, default history (if the loan has defaulted), repayment records and future repayment arrangements. Investors also benefits from the detailed borrower characteristics, including gender, age, employment, property ownership and so on. Information on the nationality and region of residence of borrowers is also available to all investors. Dey et al. (2020) document that the US localized C19 updates might be responsible to the asset price movement in stock market. However, Bondora's secondary market requires quick decisions: since the market volume is rather active, investors have only short time to explore the loans listed on the market, therefore the investor attention allocated to each loan is limited. Previous studies such as Peng and Xiong (2006) and Pantzalis and Ucar (2014) find that investors allocate more attention to the macro news compared to micro information.

Indeed, there has been flourish research focuses on the connect between the localized C19 spreads and financial market responses (e.g., Baig et al., 2021). Although the national emergency and national lockdown restrictions are issued by the central government, the localized C19 development, as well as the lockdown policy exhibit a considerable variation in Appendix FA.2.4 and TA2.12. That is, the Spanish regions had been experiencing different development of C19 outbreak, and the lockdown restriction stringencies are not the same. Therefore, it is a valuable research opportunity to examine whether the pan-European investors would dig into the localized details to facilitate their decisions.

Furthermore, wider information transmission channel is also linked to more intensive investor reaction (Aouardi et al., 2013). For instance, the variation in media coverage is associated to the drifts of asset price dynamics in US stock market (such as Bajo et al., 2016; Ozik et al., 2021). Also, the online search volume on different P2P platforms predicts the market volume of those platforms (Zhang et al., 2017). In light of these considerations, we believe that the fact that macro level C19 information plays a more important roles in P2P investor's decision-

[23] It is worth to note that, there is a significant difference between news aggregation and categorical information. Generally, news aggregation is based on the concept of content syndication, where content created by one or more news-gathering organizations is distributed through a different organization. In contrast, the categorical C19 information is issued by a single governmental resource, when it is initially published, it has been already processed and categorized. Therefore, the different response to nation- and region-wide is more related to the categorical information processing, instead of news aggregation.

making progress compared to micro news, is due to a lower media attention surrounding region-level C19 topics. If macro information is easier to search and acquire, the investors might make decisions based on sketch information. Our third hypothesis posits therefore that, in an active P2P lending environment, the media attention to the macro C19 is more significant compared to media attention to region-specific C19 topics.

Overall, we propose the following hypothesis:

H2: Investors rely more on country-specific information than region-level updates to facilitate their decisions.

2.3 Data description

2.3.1 Loan data

We collect transaction data from publicly available data provided by *Bondora*. The dataset includes primary market loan reports, which records public information for all loans over the period 2013-2020, and a secondary market dataset, which records all transactions in the secondary market from 1 October 2019 to 31 May 2020[24]. The dataset also contains a historical repayment dataset, which contains all repayment history of granted loans over the period 2013-2020. After combining these three datasets based on the unique *loan ID* numbers, we clean the dataset using following steps: First, *Bondora* mainly provide long-term loan service, therefore all loans with less than 36 months maturity are dropped.[25] Second, to explore the asset pricing dynamics on Spain-originated loans, loans created from Slovakia, Estonia and Finland are excluded.[26] Third, we eliminate the influence of outliers, by dropping the observations which in the top 1% of the distribution of discount rate in the secondary market. After removing the outliers, each loan in the dataset is matched with its repayment history and secondary market transaction information. Our final dataset includes 75,084 loan-week observations pertaining to 12,012 loans and 623,219 notes and the sample spans from 1 February 2020 to 31 May 2020.[27]

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[24] Due to Bondora removed borrowers' regional location in June 2020 according to EU data protection policy change, we only include the transaction records before this policy change occurred. This setting leads to a 4-month period. To implement the T-Test for comparing the market statistics before and after the C19 outbreak, we include 4 months before the first C19 case was confirmed in Spain. Therefore the main dataset contains observations from 1 October 2019 to 31 May 2020.

[25] Most of *Bondora* loans are created with maturity no less than 36 months. Therefore, we remove those loans with short maturity. As a result, no more than 0.001% loans are excluded.

[26] Spain is one of the 4 marketplaces of Bondora primary market. The primary loan data includes 147,093 loans covers from 2013 to 2020, of which 84,651 originated from Estonia, 26,270 created from Spain, 35,876 originated from Finland, 284 from Slovakia.

[27] In the sample period from February 2020 to May 2020, we find there are 12,012 loans. Then, these loans are traded in the market for multiple-times, generating 633,219 notes (the share of loan holdings). In the regression estimations, we aggregate the data onto loan-week level, therefore our estimation finally contains 47,005 observations (loan-week level).

2.3.2 C19 announcements

The C19 Spain-related information is extracted from public announcements published by the Health Ministry of Spain.[28] The original announcement is daily-updated at the region (autonomous community) level since the first Spanish C19 confirmed case is reported, which allows us to construct time-series for each region. The statistics of nation-wide information exerts a time-series. After merging the data using the unique region names and dropping unnecessary variables, the C19 dataset contains region name, date, number of new confirmed cases, number of new deaths. We then combine the transaction dataset and C19 dataset.[29]

2.3.3 Information transmission data

The information transmission data is proxied by online media coverage, as well as media attention. The media coverage reflects the accessibility of the information. For a particular category of information, the higher accessibility makes it easier to be accessed. Also, the demanding of information represents the investor's willingness to search and observe a certain information category.

Our first measurement simulates the media coverage by utilizing C19-tagged news dispatched throughout newspaper. The online newspaper articles have been used to represent the online attention via supply of information (such as Fang and Peress, 2009). Our media coverage measurement involves articles with C19 related tags extracted from *the aylien.com*, a professional newspaper database service.[30] We extract articles mentioning "Spain" to create the country-sample.[31] Also, news mentioning specific region names, such as "Catalonia" and "Madrid", are gathered to form the region-level sample. We capture the *Nation Coverage* by the weekly number of articles mentioning "Spain" for "Spain". Similarly, *Region Attention* is defined as the weekly number of articles mention "a region".

We implement the second measurement by assessing the online search volume. Different from the media coverage, online search volume approaches investor attention from the demand of information viewpoint (Hsieh et al., 2020). We include the online search volume extracted from Google Trends, one of the leading online sentiment analysis platforms. In particular, we extract *Google Trend Index* for "Spain" and "coronavirus", as well as a region and "coronavirus", to compare the investor attention on region- and country-level C19 information.

[28] The confirmed cases and deaths statistics are extracted from Spanish Health Ministry daily C19 announcements. https://www.mscbs.gob.es/profesionales/saludPublica/ccayes/alertasActual/nCov/situacionActual.htm
[29] Appendix FA 2.3 shows the timeline and key events related to Spanish C19 pandemic.
[30] Our C19 related tags contains tags such as "COVID-19", "coronavirus" and "covid".
[31] The newspaper and online search volume data cover the period from 1 February 2020 to 31 May 2020.

We define the *Nation Attention* as the weekly average level of *Google Trend Index* for "Spain". Similarly, *Region Attention* is defined as the weekly average level of *Google Trend Index* for "a particular region"[32].

2.3.4 Descriptive statistics

Table 2.1 presents the descriptive statistics for the loan-specific characteristics of the 12,042 P2P loans in the sample. The sample contains only loans traded in the secondary market during the period from 1 October 2019 to 31 May 2020. Indeed, the interest rate on *Bondora* is impressively high. On average, a Spanish borrower has to pay interest rate of about 65.5% on a loan. High interest rates might be the reason why default rate is rather high as well: the average default rate on Spain-originated loans is 62.4%. Precisely, there are more than 6 loans defaulting in every 10 loans granted in Spain. This suggests that funding P2P loans originated by Spanish borrowers is quite risky. When it turns to the secondary market, a P2P loan is observed to receive 43 notes per month, of which about 30 (73%) notes are successful. The majority of loans in the secondary market are sold at discounted price, with an average discount rate of 11.4%.

To have a better understanding of the impact of the C19 outbreak, in Table 2.2, we compare the asset pricing factors in pandemic with those before pandemic using a T-test. In particular, we employ the asset price measured by the discount rate of a P2P loan note, the outcome of a P2P loan note listing (success = 1; otherwise = 0), the market liquidity measured by the number of successfully sold notes normalized by the listed dates of a P2P loan. Table 2.2 shows mean differences between notes traded before and after the C19 pandemic announcement was released on 14 March 2020. Compared to the period September 2019 to February 2020, the average asset price significantly decreased by 2.4 percent points in the subsequent period. The market volume proxy significantly decreases by 0.15. The success outcome of a loan significantly increased by 29.97 percent points. These findings suggest that the C19 pandemic might be responsible to the shortage of market liquidity, downward price movements and higher probability of loans being sold.

Figure 2.1 shows the monthly evolution of several key indicators related to the investors pricing behaviour in *Bondora* secondary market, from January 2020 to December 2020. To capture the investors behavioural terms in P2P secondary market, we focus on several indicators related to asset pricing dynamics, market liquidity and agreement of valuations. We first inspect the asset

[32] For each different region, we construct an individual index for google trend.

price evolution measured by discount rate in Figure 2.1, Panel A. The average price of notes asked by sellers is about -12% in February 2020, the last month before the pandemic. This number decreases to -15% in March, the month at which the national lockdown was announced. This number remains at a low level until the end of May 2020. When we turn to the market liquidity and agreement of valuation, in Panel D, we observe the market volume proxied by the number of notes of a P2P loan increases in March 2020, then declines sharply in May 2020. The number of unique loans being listed on the market performs similarly to the number of notes. The evolution of these two factors suggests the liquidity of the market significantly shrinks after the pandemic. Panel C presents the monthly trends of successfully sold notes, differs from the other panels, Generally, a higher rate of success indicates a higher agreement of asset valuation between these two counterparties (Chatterjee et al, 2012; Carlin et al, 2014). In particular, we observe the share of success notes experiences a reasonable increase in March 2020, then slightly decreases when restrictions are lifted. Overall, the monthly evolutions provide chance to explore the relationship between pandemic and loan outcomes in P2P market.

The development of C19 outbreak is represented by Figure 2.2. The first case was confirmed on 1 February 2020. The number of new confirmed cases remained low until the local community transmission started from late February. Then the number of infections rapidly increased, during the national lockdown period from 14 March 2020 to 12 April 2020, with an average number of daily new confirmed cases of approximately 4400. The lockdown was lifted from 13 April 2020, after which the daily updates of C19 case generally decreased to around 500. The Spanish government announced restrictions to be lifted from June 2020 onwards as the daily cases remained low from two weeks. Comparing the C19 information updates and the asset price movements, we can see that C19 cases slowly developed during February, and exploded in March and early April, then generally declined to a low level. When it comes to the market indicators, the average asset price in P2P market jumps down from March, and then consistently declines until May 2020. And the success rate of transaction generally perform similarly with the C19: The evolution market indicators and C19 development suggest that, there might be a connection between the C19 information and investor decision-making.

2.4 Baseline specifications

2.4.1 Do investors react to C19 information?

Information is not directly perceptible. Therefore, one important question for empirical studies which focus on the role of information arrival in asset pricing is how to proxy the information.

The main research question of this study is whether the Spanish C19 announcements affect European investors' decisions.

To have a better understanding about investors behavioural terms on a secondary loan market, we create several indicators related to loan performance. For instance, to represent the market liquidity of the market, we calculate *No. of Notes*, the number of notes listed by the sellers normalized by the number of listed days for a P2P loan. This factor represents the daily number of listed notes for a P2P loan in the current week, and it has been used in recent empirical studies such as Rigbi (2013). Then, we use *Discount* calculated by the average price of notes (measured by the percent points of discount or premium) asked by the sellers for a specific loan. This variable helps to understand how sellers value their assets. Besides the sellers' pricing behaviour, we use *Share. of Success*, which is defined as the share of successfully notes of a loan (measured by percent points) to proxy buyers' acceptance to the sellers' pricing. This factor provides an insight of the agreement of asset valuation between sellers and buyers.

Inspired by literature investigating investors' reaction to the C19 pandemic (Alfaro et al., 2020; Baig et al., 2021), we first use the C19 announcement information and public loan and borrower information to investigate investors decision-making in a secondary loan market. In this context, the estimation that follows would be specified on loan level. Considering the daily update of C19 announcement is quite fast, this estimation is performed at a weekly level. Therefore, we run the regression below:

$$Loan\ Indicators_{i,t} = \alpha + \beta_1 Nation\ Epidemic_t + \beta_2 Region\ Epidemic_{k,t}$$
$$+Control_{i,t}\beta_3 + \varepsilon_{i,t} + u_{i,t} \tag{2.1}$$

where *i* and *t* refer to loan and week indices, respectively. *k* refers to the particular region where the loan *i* originated from. In particular, we examine loan performance indicators, *No. of Notes*, *Discount,* and *Share. of Success* captured by a vector *Loan Indicators,* to investigate investors behavioural factors.[33]

The vector *Control* includes several covariates. For instance, to quantify the effect of loan maturity, we utilize *Loan Age,* which is defined as the logarithm of one plus the maturity of the loan (see also Havrylchyk and Verdier, 2018). Loans approach maturity carry less risk as the borrowers have a proven repayment record. Hence, we expect the coefficient associated with *Loan Age* to be positive for the average asset price. Following Morse (2015), we include

[33] The definition of all variables in the paper is attached as Appendix Table TA2.9.

Outstanding Principal, the share of outstanding principle in the current week out of the original principle to control the effect of stage of loan repayment process. The coefficient associated with *Outstanding Principal* is expected to be positive for the average asset price, as the higher remaining principle normally means higher potential future repayment cash. To capture the effects of the overall market volume on the market, we include *No. Loans,* which is the logarithm of one plus number of notes being listed on the market during the current week. Generally, a higher *No. Loans* posits a greater market volume that investor is more likely to ask higher price. We therefore expect *No. Loans* to be positively related to the asset pricing term. In addition, we incorporate two types of fixed effects: a loan fixed effect and a region fixed effect to control for time-invariant loan characteristics and platform characteristics. Model (1) is estimated using a fixed effect estimator with robust standard errors.

To quantify the effect of C19 announcement, we go through the Spanish C19 announcement series and extract the objective counts: the number of confirmed cases and deaths. Recent analyses such as Phan and Narayan (2020) and Chatjuthamard et al. (2021) use the numbers of C19 case released by authorities to trace C19 outbreak. It is worth to note that, Spanish Health Ministry update confirmed cases and deaths on both Spain country and its region level. These two different proxies are released parallelly, which drives two individual information flows on country-wide and region-specific levels[34]. In light of previous literature which includes both sector-wide news and firm-specific announcements (e.g., Hirshleifer and Sheng, 2021; Liu, Peng and Tang, 2021), we extract the direct proxies of the effects of C19 announcements: two factors, *Nation Epidemic* and *Region Epidemic,* and include as them as the key explanatory variables of the model (1). The *Nation Epidemic* includes *Case Nation* and *Death Nation* capture the logarithm of 1 plus the number of C19 confirmed cases and deaths in current week in Spain. The *Region Epidemic* includes *Case Region* and *Death Region* to capture the number of C19 confirmed cases and deaths in current week in a region where the P2P loan originates.[35] The nation- and region-wide information flows provide a unique environment: if two categories

[34] Appendix Figure FA2.4 shows the variations among asset pricing terms and C19 statistics among different Spanish regions are both developing. Since investors are allowed to explore the borrowers' location, the county- and region-specific borrower location can be considered in the decision making. One would therefore expect that the growing variation among asset pricing movements between regions might be driven by the ongoing dispersion of C19 updates. Panel A of Figure 3 represents the discount in March 2020, and Panel B shows the average asset price in May 2020. We observe that the average price of notes in each region during March varies from -13.7% to -24.0%, this variation is -27.4% to -55.9% Compared to the average asset price in March, the average discount of notes in all regions drops after the start of the C19 pandemic. Also, the variations among different regions have been expanding. Interestingly, the dispersion of C19 statistics in different regions has also been expanding. Panel C represents the number of cases in March 2020, Panel D shows the number of cases in May 2020. In March 2020, the standard deviation of regional C19 confirmed cases is 13,351, this number increases to 85,047 in May 2020. In the next section, we would explore this behavioural issue by investigating the connection between asset pricing dynamics and C19 statistics at both country- and region-level.

[35] There have been studies summarize the C19 statistics on weekly level, such as Ding et al. (2020) and Khan et al. (2020).

of information are released in the same time, which category of updates would be consumed indeed?[36] In accordance with hypothesis (H1), we expect both β_1 and β_2 to be negative for the average price of assets. Furthermore, if H2 holds, we expect β_2 to be smaller than β_1.

2.5 Results

2.5.1 C19 announcements: macro vs. micro

In this section, we examine how pan-European investors response to the C19 information. We estimate the Model (1) based on the sample contains 4-month period since the first case was confirmed in Spain (1 February 2020 to 31 May 2020). The expectation is that sellers would learn the C19 announcements and adjust their investing strategies accordingly.

Table 2.3 presents the results of Model (1). Prior work of Cumming et al. (2021) has observed the volume shrink in P2P loan market since the outbreak of C19. In this case, the ongoing C19 cases raises market volume shortage and asset price drop in secondary market. For example, in column (1), Panel A, *Case Nation* is negatively associated with the number of notes. Holding all other variables constant, a 10,000 increase in weekly new-confirmed cases leads to a 0.08 decrease in the normalized number of notes of a P2P loan. This crisis-induced volume drop is also detected in cryptocurrency trading (Huynh et al., 2021). The negative relation between ongoing C19 cases and market liquidity suggest some investors might prefer to hang-on and hold their current assets. Next, in column (2), the ongoing number of cases is negatively related to *Discount*, the direct proxy of asset price. Specifically, a 10,000 increase in weekly confirmed cases is associated with a 3.0 percent points decrease in the average price of notes. Sellers tend to list their current notes at a lower price in response to the ongoing cases numbers. Considering before-pandemic average price is approximately -9.7 percent points, the negative impact of C19 announcement is substantial. Moreover, the C19 announcements spotlight the agreement among investors on the asset valuation. In column (3) a 10,000 increase in *Case Nation* leads to a 8.5 percent point increase in the *Share. of Success*. This effect is considerable as this number during the period from October 2019 to January 2020 is about 62.1 percent points.

These results support hypothesis H1. The number of cases provides direct signals to represent the development of the epidemic situation. These signals, subsequently, lead to the movements in asset valuations given by both sellers and buyers. First, the unremitted increase in confirmed cases could be pessimistically interpreted, as a result, sellers reduce their evaluation on the

[36] To figure out whether the country- and region-level statistics are correlated, we examine the correlation relationship between these two statistics. The region and country-level information indices are mediately correlated, the correlation matrix is provided in Appendix Table TA2.10.

asset value based on the negative signals from C19 announcements. Consistent with Ding et al. (2021), the increasing number of confirmed cases is responsible to the downward drifts in asset valuation since the C19 outbreak. Second, the higher success rate of listed transaction indicates both sellers and buyers hold negative anticipation to the asset price movements. Ölvedi (2021) also captures the high success rate in Bondora secondary market since the pandemic. The adverse interpretation on the increasing C19 cases is not given by sellers only, buyers are also reducing their expectation on the asset price, they are willing to take the opportunity to purchase asset at a lower price. It is also worth to notice that C19 announcement mainly drives the investor decision on the asset valuation, when it comes to the decision on whether to detach the loan note, the C19 outbreak could only play finite contribution.[37]

Besides the borrowers' nationality, *Bondora*'s settings allow investors to check borrowers' regional residence.[38] The baseline estimation suggests the local epidemic spreads also contributes to the asset price drifts. Loans with higher exposure to local covid spreads are more likely to be reduced. In column (1), the region-level confirmed cases exerts in-significance to *No. of notes*. The detailed information will not change sellers' decision on whether to put this asset on the market. In column (2)-(3), a 10,000 increase in the regional cases can leads to a 0.9 percent point decrease in the average price and a 2.7 percent points increase in the valuation agreement. That is, the information on local spreads, could also cause downward asset price drifts (see also Dey et al., 2022; Au et al., 2020). When it comes to the information categories, we observe borrower-specific local news presents smaller sequential correlation on the loan indicators compare with macro updates.

This result is rational and consistent with pioneering works. In this study, secondary market provides an information environment in which investors could rely on Spain, the nationality, as well as the loan-specific borrower location to facilitate their decisions. Previous works such as Lamont and Stein (2006) find that equity issuance and mergers rely more on aggregate market price than firm-level stocks. Heimfarth et al. (2012) suggest the hedging effectiveness estimated on the aggregated level is higher than the individual farm-level estimations. Our estimation demonstrates that EU investors process more aggregate nation-wide information rather than the updates related to the specific region from which the loan originated. This

[37] We attached a coefficient plot which involves in the interaction between weekly infections and week dummy (See Appendix FA.2.5). It is observed that the effect of C19 cases on each loan indicators are generally consistent in the entire pandemic phase. In the early stage of COVID-19 pandemic, the investors react to the updates of C19 news. Although the effect of C19 cases slightly moderates after then pandemic develops for few weeks, the size of effect is still considerable.

[38] The regressions cover from 1 Feb 2020, at which the first case confirmed in Spain, to 31 May 2020, at which Bondora eliminates the region-specific location of borrowers due to EU data protection policy.

finding supports our hypothesis H2. Since the regional and national statistics are synchro-updated, one might possibly interpret that macro news related to epidemic development is more likely to be acquired by ordinary individual investors.

This estimation also includes the epidemic information related to C19-induced deaths. Table 2.3, Panel B presents that the economic significance of death information is quantitatively similar on country-level cases information. However, a certain number of deaths is often accompanied by a much larger number of confirmed cases.[39] For instance, on 13 March 2020, the date when Spanish national emergency status was announced, there were 7,627 confirmed infected cases with 49 people reported dead by C19. Therefore, the economic significance of *Death Nation* in column (2) and (3) is smaller than that of confirmed cases. Also, the correlation matrix in Table TA2.11 provides an insight that the number of deaths is highly correlated to the number of confirmed cases. The estimates on infections and deaths are in line with the argument of Baig et al. (2021), that investors rely more on information related confirmed cases, rather than deaths to facilitate their decisions.

The signs of the control variables are as expected. For instance, in column (1), Panel A, Table 2.3, the *Outstanding Principal* exert insignificant correlation to the market liquidity indicator, which suggests the process of the loan repayment does not affect the trading frequency of the loan. However, the *Outstanding Principal* is negatively related to the asset pricing terms. It is sensible that the higher remaining principal normally provide more future repayment, therefore holders of those loans might be willing to keep them for a while to receive the loan repayment (see also Caglayan et al., 2021a). Also, when the loan approaches the later stages of its progress (with higher *Loan Age*), investors are not in to sell the asset. Indeed, investors tend to ask a higher price to earn a "age premium." Existing studies (e.g., Warga, 1993; Perraudin and Taylor, 2003) have investigated this "age premium". In loan secondary market, loans have longer mature have proven a reliable repayment history, suggesting the risk of the loan is lower.

Additionally, when the market is more active (with higher *No. Loans*), investors are more likely to ask higher price of their asset. Prior studies (e.g., Chandrapala, 2011) document the stock returns are positively related to the increase in trading volume. Similarly, our finding suggests high market volume helps asset holders identify the momentum of the market, they might believe their assets would be more easily to be purchased. Also, due to the buyers' have only limited attention, the high-volume might enforce investors spend less attention to a particular

[39] The number of deaths and number of infections are moderately correlated on both country and region level. We examine the correlation relationship in Appendix Table TA2.11.

loan, the asset might be more likely to be accepted. The economic significances of control variables are quantitatively in both Panel A and B.

2.5.2 Does information transmission channel affect investor decisions?

Regarding the evidence that investors allocate less attention to region-level information, in this section we explore potential explanation of this phenomenon. Indeed, we propose the inattention might be attributable to the limited media attention on regional epidemic issues. Under the limited attention, investors tend to make decisions based on macro level information (Peng and Xiong, 2006). Meanwhile, the secondary market trading volume is quite active, investors must make quick decision under limited attention. Hence, it might be difficult for investor to assess detailed information. We hereafter extend the literature on limited investor attention by explicitly incorporating categorical C19 information on region- and nation-level, as well as the transmission channels of C19 information.

To proxy the media coverage from the perspective of information supply, we assess the newspaper articles extracted from the *aylien.com* coronavirus newspaper database. Besides, we also measure the investor attention via the demand of information proxied by the Google Trends on Spain and it's region C19 topics. In particular, the Spain-C19 index is selected as the benchmark of attention on each region. We re-estimate Model (1) using *Nation Attention* and *Region Attention*, i.e. the number of C19 topic news related to nation-wide and region-specific terms.[40] The C19 information, *Case Nation* and *Case Region* are also controlled in estimation. The dependent variables and other explanatory variables remain the same settings as model (2). As we propose the media attention channel is responsible to the categorical reaction to C19 news, we first expect the media attention on macro and micro level exerts different roles to investors' pricing. We also expect the explanatory power of C19 announcements reduces after introducing the media attention.

The results reported in Table 2.4 document that the inattention on region-level C19 news is associated to the insignificant media coverage on regional C19 updates. Specifically, column (1) shows the *Nation Coverage* has limited significance to the number of listed notes, which suggest the media coverage is weakly related to the market volume. Yet, the media coverage effect on asset price is larger than the impact on market liquidity. In column (2), the asset price is negatively associated with the *Nation Coverage.* Generally, on loan-weekly basis, 10 points increase in *Nation Coverage* leads to a 1.5 percent points decrease in average note price of a

[40] Descriptive statistics of proxies for *Nation Attention* and *Region Attention* are attached in Appendix Table TA12.

P2P loan. When there is more Spain C19-related news, the sellers are more likely to reduce the listing prices of their current assets. That is, the asset pricing dynamics is also driven by the media coverage, higher coverage to bad news would depress seller's valuation on their loan holdings. In addition, buyers make the similar interpretation to the change in information supply. Specifically, the agreement on asset valuation is positively related to the *Nation Coverage* in column (3). This finding further confirms that sellers and buyers make the same direction judgements based on the information exposure.

Compared to the effects of media coverage on Spain, the information supply on regional scale is in-significant to the sellers pricing strategy and buyers asset valuation. In columns (1)-(3), the *Region Coverage* is statistically insignificant to the market volume, asset price and agreement on asset valuation. Previous theories such as Kacperczyk et al. (2016) show that investors tend to allocate less attention on micro-level news during periods with high-uncertainty. Our results suggest that the supply of micro-level information is insignificant to the investor decisions. When the investors make decisions, their judgements rely on the accessible information relates to Spain the nation, the news and media posts detailed on the Spanish regions might not be consumed by the investors.

It is worth to note that, after including the media coverage factors, in column (1), the influence of media coverage on the market volume is rather weak, which suggest that sellers barely adjust their willingness to sell their asset based on the media news streams. In contrast, the significance of *Case Nation* in both column (2), (3) decrease compared to the baseline estimations. In contrast, the *Case Region* remains the similar significance compared to the baseline test. These signals could lead to two possible interpretations. First, the information coverage of nation-wide C19 topics might be a transmission channel in which the C19 announcements on Spain-wide could be passed throughout internet and drive investors decisions. Both sellers and buyers make use of the news dispatched by online media to value the Spanish assets. Second, the online media coverage about regional updates is insufficient to affect investor's decision making, investors rarely adjust their valuation on the assets according to the online exposure via news and articles related to specific regions.

Besides the media coverage, we also arrange an estimation based on the media attention. This estimate could help to understand whether investors have limited willingness or motivation to search details. We therefore replace *Nation Attention* and *Region Attention* by the Google trend index on C19 topics related to nation-wide and region-specific terms, respectively. The results presented in Table 2.5 are quantitatively similar to the findings in Table 2.4. The demanding of C19 information exerts categorical significance on macro and micro level, and the significance of Spain nation-level confirmed cases is eaten-up by the media attention on the country. Investors have significant demanding to the distinct signals on macro, yet they have limited interest to dig into the details and figure out the nuance.

These results demonstrate that, the inattention on the region-level C19 information might be driven by the limited media attention. These findings complement the literature, which argues the limited attention on macro and micro information (Hirshleifer et al., 2021). First, the information environment in which C19 related news is created and passed does not contain sufficient detailed information on region-specific level. The limited supply of details makes it easier to reach and handle the information about what happens to Spain, the country, whereas recognizing regional updates is more difficult. Second, the investors are not really interested in micro issues, therefore they are not active to rely on detailed information (e.g., Peng et al., 2007). They might have willingness to know what happens to the Spain country, whereas a Spanish region, especially a small region, is too concrete to know. Overall, the inattention on region-specific C19 announcement can be explained by the insufficient media attention on region-specific topics: news on micro is more likely to be missed or ignored on the Internet.

2.5.3 Does C19 information mitigate the mismatched asset valuation?

In the baseline estimation, we have the evidence of the impact of C19 information on asset valuation agreement between sellers and buyers. To have a better understanding of whether the C19 information drives investors make contiguous downward asset valuation, we capture the mismatched asset valuation between sellers pricing and buyer. This mismatch on asset valuation between sellers and buyers have been investigate in recent empirical studies (e.g., Lewis et al., 2021; Da Costa et al., 2013).

Following Caglayan et al. (2021a), we first estimate the probability of the outcome (success or not) of each note listed on the market. Generally, a high-predicted probability of being sold might be considered as the seller's pricing is near the initial price where the asset should be (Walking, 1985). Whereas a low-predicted sold probability indicates the seller overvalue the price of asset. The probability of asset transaction outcomes (success = 1, fail = 0) is given by a machine learning framework, least absolute shrinkage and selection operator (LASSO). LASSO is used to predict an asset's sale outcome based on the information of the asset. We then compare the predicted probability of being sold of each note with its actual selling result. If a note with low-predicted probability is successfully sold, it means the buyer's pricing exceeds seller's pricing. In contrast, if a high-probability note is actually failed, we interpret the buyer's valuation is higher than seller's asked price.

In this context, we define the *Type 1 error* as a low-probability (lower than 0.25) asset successfully being sold. In contrast, *Type 1 error* suggests a high-likelihood (higher than 0.75) asset fails to be sold. To proxy investors' asset mispricing terms, we include *Share. Type 1 error*, defined by the share of Type 1 error of a P2P loan in the current week. Also, *Share. Type 2 error* is included to capture the share of Type 2 error of a specific loan. The t-test inTable 2.2 provide a preliminary insight of the movements of mispricing terms. Compared to the pre-pandemic period, the type 1 error and type 2 error significantly decreases after the outbreak of C19.

suggest that the C19 updates might triggers the movements of mismatched beliefs of sellers and buyers. In column (2), *Share. Type 1 error* does not react to the epidemic information as the updates of both region and country level C19 information are insignificant. This phenomenon could be explained by the loans with low-predicted probability being sold cannot attract more buyers' attention due to their poor quality. On the contrary, column (3) shows the *Share. Type 2 error* is negatively related to the C19 update as the increase in both region and nation level C19 information updates would drive the decrease in *Share. Type 2 error*. The narrowed mismatched belief, extends the baseline understanding as the average asked price given by sellers dramatically decrease with the ongoing C19 outbreaks. This evidence illustrates that both sellers and buyers have the downward forecast to the asset valuation, which makes low-priced P2P loans are more likely to be agreed by the buyers. Overall, the C19 related information mitigates the mismatch between sellers and buyers on asset valuations.

2.5.4 Extensions

2.5.4.1 The role of lockdowns in investor decision-making

The examination on H1,2 provides an insight that C19 announcement could drive the investor decisions. Besides the official C19 announcement, lockdown restriction is another information proxy of C19 development. There has been evidence that banks with higher exposure to economic lockdowns are more likely to experience non-perform loans (Beck and Keil, 2022). Also, the economic lockdown policies affect investors expectation of borrowers' repayment capability (Malik et al., 2020). *Bondora* investors are sensitive to borrowers' payment capacity as the platform allows them to purchase loans at discount to seek profit in loan repayment and recovery process (Caglayan et al., 2021a). Therefore, it is meaningful to examine whether the asset price drop is also associated to the information related to lockdowns.

We propose that the downward asset price drifts are also attributable to the economic lockdowns. In particular, more intensive lockdown is expected to be associated with lower asset prices.

Since the outbreak of C19, the mobility has been considered as one of the direct proxies of the stringency of lockdown restriction (Spelta et al., 2020). Hence, this study uses the mobility indices provided by *Apple Inc*. to proxy the lockdown stringency.[41] In particular, we use the Coronavirus Mobility Report released by *Apple.Inc*. The lockdown imposed by Spanish central government enforce economic operating under restriction. The mobility indices represent the impact of economic lockdown (e.g., Hadjidemetriou et al., 2020, Gupta et al., 2020; Spelta et al., 2020). Overall, the C19 announcement series and Apple mobility index obtain both national and regional information covers the period from 1 Feb 2020 and 31 May 2020.

We adjust Model (1) by including the mobility index terms, *Region Mobility* and *Nation Mobility*. In particular, *Region Mobility* and *Nation Mobility* presents the average mobility index in current week in a particular region and Spain country, respectively.[42] Throughout the movements of mobility index, one could observe how stringency of lockdown polices changes. Furthermore, to examine whether the economic lockdowns enhance the effects of C19 information on investor decisions, we include the interaction terms *Region Mobility* Case Region* and *Nation Mobility* Case Nation*.

The results in Table 2.7 suggest the lockdown contributes important implications on the negative asset price change on P2P secondary market. In column (2) and (3), after including the lockdown stringency parameters, the *Case Nation* and *Case Region* remain the similar significance as the baseline estimation. Further, the *Nation Mobility* is positively related to asset prices as a 1 percent point decrease in Spain mobility leads to a 0.2 decrease in the average price of notes for a P2P loan. Moreover, the *Nation Mobility* exerts negative effect on the asset valuation agreement. One might possibly interpret that the lockdown-induced low mobility might also be associated to the mitigated mismatched beliefs on asset valuation (see also Bretscher et al., 2020). More specifically, buyers emit the accordant valuation with sellers when the lockdown is restricted. Similar to the media attention on region-specific C19, the localized mobility does not affect investors decisions. The interaction term on nation-level C19 statistics and mobility are negatively related to the average price of assets, which suggests the

[41] The Apple coronavirus mobility report sets up the mobility level in January 2020 as index baseline (100 percent point). It provides localized mobility index for each region of Spain since January 2020.
[42] Descriptive statistics of proxies for *Nation Mobility* and *Region Mobility* are attached in Table TA2.12.

higher Spain mobility could depress the negative effect of C19 announcement on asset price. Our estimations provide consistent evidence that, the intensive lockdown restriction might enhance the C19-induced downward asset price drifts (Davis et al., 2020; Saito and Sakamoto, 2021).

2.5.4.2 The role of C19 information from high-infected areas

Recognizing investors allocate more attention to nation-wide information compared to regional updates, we consider whether there are special areas out of those 19 regional subdivisions draw more attention. Madrid region (it is named by Madrid city, the biggest city in Spain) and Catalonia region (famous for its capital Barcelona, the second biggest city in Spain), provide 40% GDP and 30% population of Spain. [43] Apart from the economic and population, those two regions are the top two infected regions in Spain (New York Times, 2020). In this context, we consider whether investors would acquire more information related to these two most infected areas. Therefore, we implement an interaction term to capture whether loans created from most-infected regions are affected by the regional information flows. In particular, we create two groups by the loan origination. We first select loans originated from Madrid and Catalonia. These two regions are labelled as *Most-infected Regions* (ranked by cumulative confirmed cases by 31 May 2020).

The results of Table 2.8 present the estimations based on the interaction. In columns (1)-(3), the categorical C19 announcements, *Case Nation* and *Case Region* perform as the baseline estimation. Furthermore, the interaction between *Case Region* and *Most-infected Regions,* is statistically insignificant to investor decision indicators in column (1)-(3). On the contrary, the interaction between *Case Nation* and *Most-infected Regions,* are positively significant to the asset pricing term in column (2). Early study (e.g., Samles, 2020; Peltomäki et al., 2021) suggests the reaction to C19 information might varies from industrial sectors, we demonstrate the investor reaction differs from the sub-division areas. One might possibly interpret that, for loans originated from most-infected areas, the negative effect of *Case Nation* is “nibbled”, therefore the nation-specific information plays less importance on loans created from Most-infected areas. That is, compared to the abridged effect of nation-wide announcement, the regional C19 information related to those *Most-infected Regions* would be likely to play more important roles in investors pricing strategy. Besides the asset pricing terms, investors are not

[43] The data about population and GDP of each region in Spain is obtained from the public report released by Spanish Statistical Office (INE).

likely to These findings indicate that information related to most infected regions might be more focused.

2.6 Conclusion

Do P2P investors react to the C19 related information? Do macro news or micro news dominate investors' decisions? To answer these questions, we evaluate the link between C19 information and asset pricing dynamics. Using data extracted from a prominent European P2P lending platform, we provides evidence that pan-European P2P investors exhibit negative pricing movements in response to Spanish C19 announcements. We also find a stronger effect of country-level C19 news compared to regional level news. We explain this bearing in mind that investors pay less attention to regional C19 updates.

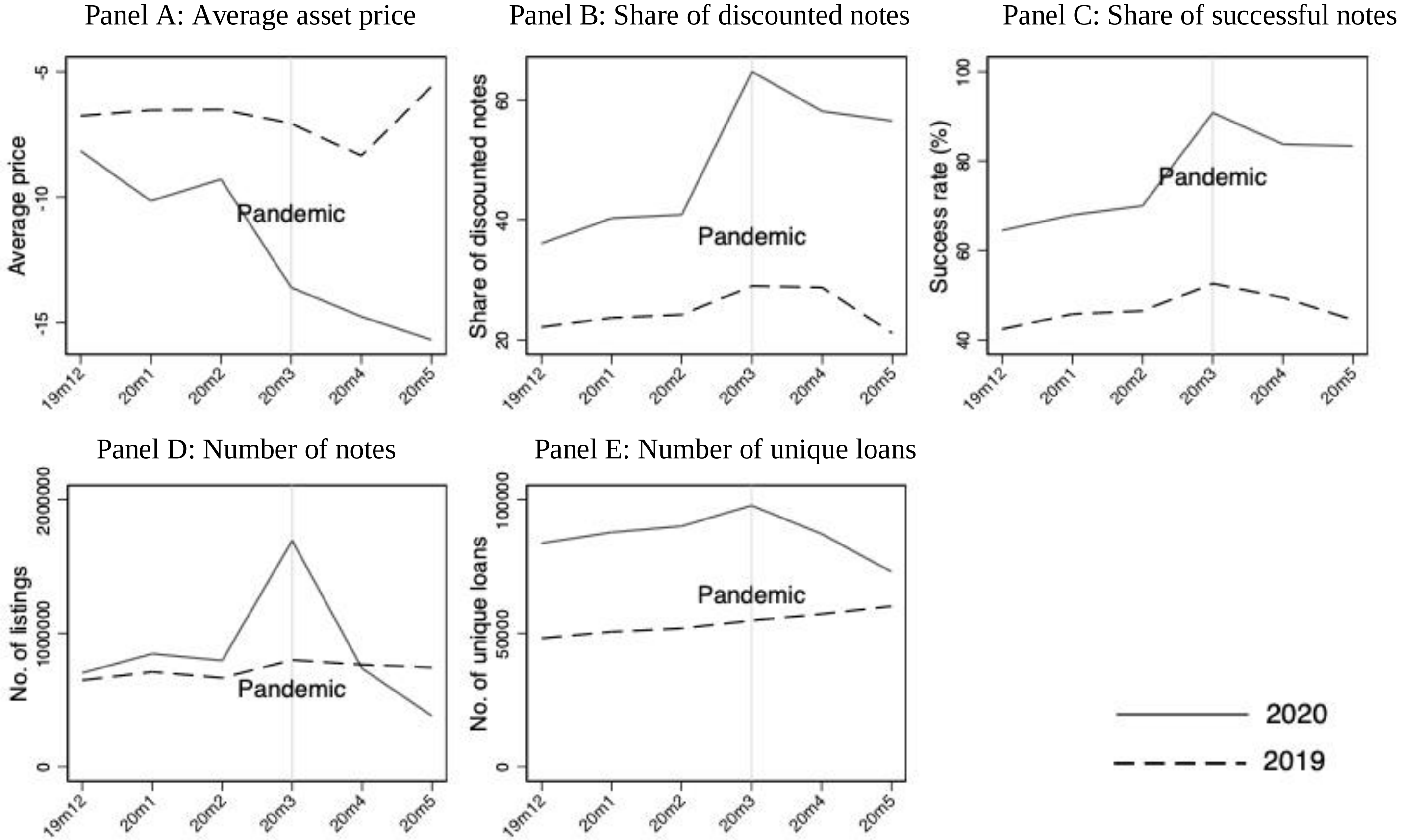
This paper contributes to the literature in three ways. First, we complement the literature focused on the public information and asset pricing in financial market (Lillo et al, 2015 and Morse, 2015). We assess the reaction of unprofessional investors to the indirect information released by non-economic authorities. Second, this paper adds to the empirical studies investigating the role of investor inattention (Tetlock, 2007, Zhang et al, 2013 and Vozlyublennaia, 2014). Utilizing parallel macro and micro media attention proxies, we conduct that the inattention on regional terms is associated to the insufficient micro media attention and limited information supply Third, this paper adds to the literature focuses on the negative effects of C19 crisis on a P2P financial market. We document the C19 announcements triggers the shortage in market volume and asset value in a P2P secondary platform.

In this study, we find the following. First, we find that, in response to the negative information about ongoing C19 updates, sellers ask lower prices and list fewer notes. Moreover, investors react more to nation-wide information than region details. We explain this finding by the higher media attention surrounding national rather than regional updates. In two extensions, we find that investors focus more on information related to large than small cites. Finally, we find that periods of economic lockdown accentuated the negative drifts of asset pricing.

This study provides several implications. First, the inattention to loan-specific C19 information could be explained by the limited media attention channels on regional-updates. Individuals have limited capability to learn and process all information flows passed throughout the internet. Second, the effect of macro-level information is prominent in the investor decision-making progress. The loan-specific location is not important to the investors during the special event period. Third, P2P secondary market is a growing marketplace which attracts more and more investors, the risk of investing in secondary market should be sufficiently noticed when investors register and invest. These implications call for more deep investigations of the role of information arrival in P2P lending markets.

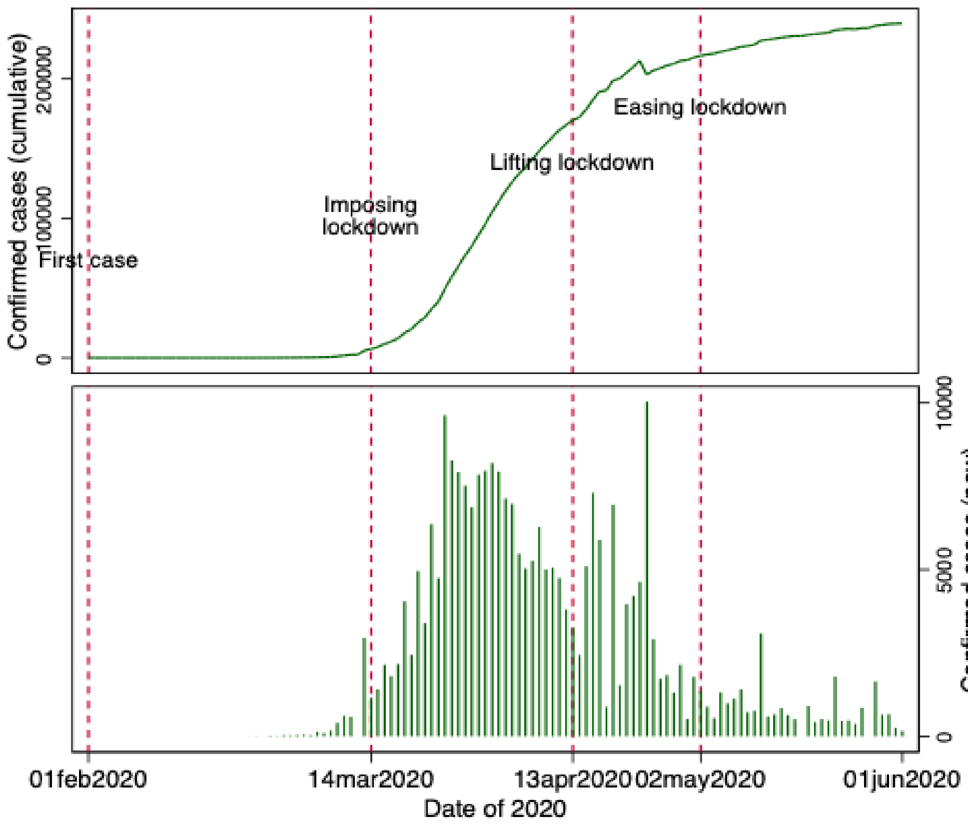
Figures

Figure 2.1: Descriptive statistics by month: Spanish Loans



This figure shows the average price of notes (the price of asset in this chapter means the asked discount rate given by the sellers), share of discounted notes, average success rate, number of secondary market loans, number of unique loans in the secondary market over the examined period. Y-axis in all plots represent the units of descriptive statistics, respectively. X-axis in all plots represent the months before and post the pandemic. In particular, February 2020 is the first month of the C19 outbreak and the March 2020 is the month when the pandemic started. Solid lines represent the statistics for 2020 period, dashed lines represent the statistics for the same period one year before. The left vertical lines represent February 2020 or 2019, the right vertical lines represent July 2020 or 2019.

Figure 2.2: Cumulative & new infections in Spain (daily basis)



Note: The above box of this figure represents the cumulative confirmed cases in Spain during the time period from the first case was confirmed at 1 February, 2020 to 1 June 2020. The below box represents daily new-confirmed cases in Spain from 1 February 2020 to 1 June 2020.

Tables

Table 2.1: Descriptive statistics for P2P loan

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	p25	p50	p75	Std	Obs.
Original Principal	1,987.320	800.000	2,125.000	2,126.000	1,415.980	12,042
Default	0.691	0.000	1.000	1.000	0.462	12,042
Interest Rate	65.258	40.400	57.760	73.730	39.563	12,042
Maturity	51.114	36.000	60.000	60.000	10.925	12,042
Share. Unpaid	0.007	0.001	0.003	0.006	0.033	12,042

Note: This table reports the descriptive statistics for all loans which are originated in Spain. *Original Principal* represents the principle amount of loan (measured in Euro). *Default* is a dummy variable measures the outcome of loan, which equals to 1 if the loan is recorded as default or 0 otherwise. *Interest Rate* represents the interest rate (in percentage) for loans. *Maturity* represents the maturity of loans (measured in months). *Share. Unpaid* represents the ratio of the note's principal to the original principal when the note is listed in the P2P secondary market. *Discount Rate* is the discount rate or premium rate (mark-up) rate asked by sellers.

Table 2.2: t-tests: P2P notes before vs. post pandemic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean	Std	Obs	Mean	Std	Obs	
	Before Pandemic			Post Pandemic			Diff
Discount	-15.574	25.155	114,378	-18.01	23.383	75,804	-2.435***
Share. of Success	53.796	44.318	114,378	83.769	33.480	75,804	29.973***
Notes	1.517	1.835	114,378	1.367	1.244	75,804	-0.149***
Share. Type 1 error	0.369	5.150	114,378	0.203	4.450	75,804	-0.166***
Share. Type 2 error	6.626	23.681	114,378	0.877	9.116	75,804	-5.749***

This table represents the t-test for mean difference between notes before the C19 pandemic and after the C19 global pandemic (14 March 2022). *Discount* (%) represents the discount rate / premium rate asked by the sellers in secondary market. *Success* represents the share of number of successfully sold notes for a P2P loan. *No. of Notes* represents the number of notes listed on the secondary market for a P2P loan. *Share. Type 1 error* is defined by the share of Type 1 error of a P2P loan in the current week. *Share. Type 2 error* is included to capture the share of Type 2 error of a specific loan.

Table 2.3: Investor reaction on country- and region-level information

	(1)	(2)	(3)
Panel A: investor reaction on infection-related information			
	No. of Notes	**Discount**	**Share. of Success**
Outstanding Principal	0.1907	-23.1688***	37.9615***
	(0.1550)	(2.2706)	(3.5833)
No. Loans	0.2779***	2.7567***	1.1076***
	(0.0141)	(0.2063)	(0.3256)
Loan Age	-0.4630***	6.8363***	-27.5429***
	(0.0347)	(0.5088)	(0.8029)
Case Region	-0.0015	-0.1872***	0.5472***
	(0.0028)	(0.0405)	(0.0639)
Case Nation	-0.0152***	-0.6000***	1.7055***
	(0.0037)	(0.0536)	(0.0846)
Observations	75,804	75,804	75,804
R-squared	0.2153	0.5090	0.4222
Panel B: investor reaction on death-related information			
Outstanding Principal	0.1970	-22.3743***	36.3685***
	(0.1582)	(2.3131)	(3.6822)
No. Loans	0.2709***	2.5258***	0.9103***
	(0.0141)	(0.2063)	(0.3284)
Loan Age	-0.4731***	8.9051***	-32.0410***
	(0.0357)	(0.5225)	(0.8317)
Death Region	-0.0020	-0.0818	0.0747
	(0.0035)	(0.0507)	(0.0807)
Death Nation	-0.0068*	-0.5386***	2.0738***
	(0.0036)	(0.0532)	(0.0847)
Observations	75,804	75,804	75,804
R-squared	0.2162	0.5141	0.4243

This table present the results for model (1) with *No. of Notes, Discount* and *Share. of Success* as the dependent variable in Panels A and B, respectively. *No. of Notes* is the number of current listings normalized by the number of listing days in the current week. *Discount* is the average price of the notes of a given loan asked by sellers in the current week. *Share. of Success* is the share of successfully sold notes out of all notes for the same P2P loan in the current week. Panel A and B present the estimation of the effect of confirmed cases and deaths on loan indicators, respectively. *Death Region* and *Case Region* present the logarithm of number of death cases and confirmed cases in a particular region of Spain, respectively. *Death Nation* and *Case Nation* present the logarithm of number of death cases and confirmed cases in Spain, respectively. *Loan Age* is the logarithm of 1 plus the age of loans (in months). *Outstanding Principal* is the ratio of the outstanding principal in the given week to the original principal. *No. Loans* presents the logarithm of number of notes being listed on the market in the week. In all estimations, loan fixed effect, month fixed effect and region fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 2.4: Media coverage: region- vs. county-level (newspaper articles)

	(1)	(2)	(3)
	No. of Notes	**Discount**	**Share. of Success**
Outstanding Principal	-0.0654**	-23.2791***	38.3675***
	(0.0311)	(2.2709)	(3.5802)
No. Loans	0.0825***	3.1004***	-0.9819***
	(0.0033)	(0.2384)	(0.3758)
Loan Age	-0.1144***	6.8713***	-27.2804***
	(0.0070)	(0.5108)	(0.8052)
Case Region	-0.0002	-0.1796***	0.5362***
	(0.0006)	(0.0406)	(0.0641)
Case Nation	-0.0074***	-0.3891***	0.5509***
	(0.0012)	(0.0888)	(0.1400)
Region Coverage	-0.0027	-0.1303	-0.9113***
	(0.0022)	(0.1607)	(0.2533)
Nation Coverage	0.0202***	-0.7472***	4.8384***
	(0.0037)	(0.2691)	(0.4243)
Observations	75,804	75,804	75,804
R-squared	0.2542	0.5091	0.4234

This table present the results for media attention estimation with *No. of Notes*, *Discount* and *Share. of Success* as the dependent variable in Columns 1-3. The set of dependent variables are the same as Table 2.3. Control variable are the same set as Table 3. *Nation Coverage* presents the number of articles mention Spain and C19 tags. *Region Coverage* presents the number of articles mention a particular region name and C19 tags. Other independent variables remain the same settings in Model (2). In all estimations, loan fixed effect and region fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 2.5: Media attention: region- vs. county-level (Google trends)

	(1)	(2)	(3)
	No. of Notes	**Discount**	**Share. of Success**
Outstanding Principal	-0.0676**	-23.3624***	37.8996***
	-0.0312	-2.2691	-3.5972
No. Loans	0.0269***	7.6645***	-10.0325***
	-0.0035	-0.2583	-0.4095
Loan Age	-0.0810***	4.5805***	-20.1234***
	-0.0064	-0.4698	-0.7447
Case Region	0.0007	-0.2613***	0.7462***
	-0.0006	-0.0401	-0.0635
Case Nation	-0.0062***	-0.4720***	2.0279***
	-0.0007	-0.0512	-0.0811
Region Attention	0.0005***	-0.0337***	0.0526***
	-0.0001	-0.0075	-0.0119
Nation Attention	0.0018***	-0.1510***	0.3412***
	-0.0002	-0.0113	-0.0179
Observations	75,804	75,804	75,804
R-squared	0.2523	0.5096	0.4176

This table present the results for media attention estimation with *No. of Notes, Discount* and *Share of. Success* as the dependent variable in columns 1-3. The set of dependent variables are the same as Table 2.3. Control variable are the same set as Table 3. *Nation Attention* presents the Google trend for Spain C19 topics. *Region Attention* presents the Google trend indices for C19 topics in a particular region. Other independent variables remain the same settings in Model (2). In all estimations, loan fixed effect and region fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 2.6: Mismatch on asset valuation during C19 pandemic period

	(1)	(2)	(3)
	Share. error	**Share. Type 1 error**	**Share. Type 2 error**
Outstanding Principal	-1.3407	-1.0618*	-0.2789
	-1.2915	-0.5498	-1.1703
No. Loans	-0.1573	-0.0512	-0.1062
	-0.1173	-0.05	-0.1063
Loan Age	1.8149***	0.2351*	1.5798***
	-0.2894	-0.1232	-0.2622
Case Region	-0.0932***	0.0154	-0.1087***
	-0.023	-0.0098	-0.0209
Case Nation	-0.0512*	0.0225*	-0.0737***
	-0.0305	-0.013	-0.0276
Observations	75,804	75,804	75,804
R-squared	0.2139	0.1801	0.2219

This table present the results for model (2.1) with *Share. error, Share. Type 1 error* and *Share. Type 2 error* as the dependent variables. The set of independent variables are the same as Table 2.3. In all estimations, loan fixed effect and region fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 2.7: Another information proxy: lockdown restrictions

	(1)	(2)	(3)
	No. of Notes	**Discount**	**Share. of Success**
Outstanding Principal	-0.0659**	-23.4905***	38.2492***
	(0.0311)	(2.2629)	(3.5707)
No. Loans	0.0884***	4.0870***	-1.0875***
	(0.0030)	(0.2186)	(0.3449)
Loan Age	-0.1157***	6.7707***	-27.6074***
	(0.0070)	(0.5077)	(0.8012)
Case Region	-0.0030***	-0.2076***	1.1336***
	(0.0010)	(0.0725)	(0.1144)
Case Nation	-0.0011	-0.5533***	0.6971***
	(0.0009)	(0.0652)	(0.1029)
Region Mobility	0.0001	-0.0009	-0.0039
	(0.0001)	(0.0069)	(0.0108)
Nation Mobility	-0.0008***	0.2254***	-0.2931***
	(0.0002)	(0.0140)	(0.0221)
Case Region* Region Mobility	-0.0000***	-0.0005	0.0080***
	(0.0000)	(0.0007)	(0.0011)
Case Nation* Nation Mobility	0.0001***	-0.0226***	0.0206***
	(0.0000)	(0.0012)	(0.0019)
Observations	75,678	75,678	75,678
R-squared	0.2542	0.5115	0.4261

This table present the results for lockdown estimation with No. of Notes, Discount and Share. of Success notes as the dependent variable in Columns 1-3. The set of dependent variables are the same as Table 2.3. Control variable are the same set as Table 2.3. Region Mobility presents the mobility index in a particular region of Spain. Spain Mobility presents the mobility index of Spain nation. In all estimations, loan fixed effect and region fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 2.8: Information related to high-infected regions

	(1)	(2)	(3)
	No. of Notes	**Discount**	**Share. of Success**
Outstanding Principal	0.1906	-23.1734***	37.9480***
	(0.1550)	(2.2705)	(3.5834)
No. Loans	0.2781***	2.7628***	1.1027***
	(0.0141)	(0.2063)	(0.3256)
Loan Age	-0.4669***	6.6846***	-27.4004***
	(0.0349)	(0.5113)	(0.8070)
Case Region	-0.0036	-0.2712***	0.5967***
	(0.0034)	(0.0499)	(0.0787)
Case Nation	-0.0150***	-0.5912***	1.7123***
	(0.0038)	(0.0562)	(0.0886)
Case Region*Most Infected Region	-0.0001	-0.0032	-0.0408
	(0.0036)	(0.0526)	(0.0831)
Case Nation*Most Infected Region	0.0055	0.2204***	-0.1239
	(0.0055)	(0.0811)	(0.1279)
Observations	75,804	75,804	75,804
R-squared	0.2153	0.5091	0.4222

This table present the results for the estimation of most-infected regions with *No. of Notes*, *Discount* and *Share. of Success* as the dependent variable. The set of dependent variables and control variables are the same as Table 2.3. *Case Region*Most Infected Region* represents the interaction term between *Case Region* and *Most Infected Region*. *Case Nation*Most Infected Region* represents the interaction term between *Case Nation* and *Most Infected Region*. Other independent variables remain the same settings in Model (2). In all estimations, loan fixed effect and region fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Appendix

Appendix Table TA2.9 illustrates the definitions of variables appear in this analysis.

Appendix Table TA2.10 presents the correlation matrix on country- and region-level C19 indices.

Appendix Table TA2.11 presents the correlation matrix for confirmed cases and deaths information flows.

Appendix Table TA2.12 illustrates the descriptive statistics for C19 related information.

Appendix Table TA2.13 reports the Robustness check for fixed effect regressions.

Appendix Figure FA2.3 reports the timeline of COVID-19 outbreaks in Spain from 1 February 2020 to 1 June 2020.

Appendix Figure FA2.4 represent the region-level variations of C19 infections in Spain (from March 2020 to May 2020).

Appendix Figure FA2.5 reports the revolution of the COVID-19 effects on asset pricing dynamics.

Table TA2.9: Definitions of variables

Variable	Definition
No. of Notes	The number of current notes normalized by the number of listed days in the current week for a P2P loan.
Discount	The average notes price (discount rate measured by percentage) asked by the sellers in the current week for a P2P loan.
Share. of Success	The share of notes sold successfully of the same loan during the current week.
Share. Type 1 error	The share of notes listed by type 1 error for the same loan during the current week.
Share. Type 2 error	The share of notes listed by type 2 error for the same loan during the current week.
Share. error	The share of notes listed by type 1 or type 2 error for the same loan during the current week.
Loan Age	The logarithm of one plus the maturity of the loan (measured in months)

Outstanding Principal	The share of outstanding principle in the current week out of the original principle
No. Loans	The natural logarithm of one plus the number of current notes posted by the sellers on the secondary market in the current week
Share. Unpaid	The ratio of the note's principal to the original principal when the note is listed in the P2P secondary market.
Nation Mobility	The mobility level of the Spain country (normalized by the benchmark in January 2020).
Region Mobility	The mobility level of a particular Spain region (normalized by the benchmark in January 2020).
Nation Coverage	The number of C19-related news articles which mention Spain country.
Region Coverage	The number of C19-related news articles which mention a Spanish region.
Nation Attention	The Google trend index for Spain C19 topic.
Region Attention	The Google trend index for C19 topic in a particular Spanish region.
Case Nation	The logarithm of 1 plus the number of confirmed cases caused by C19 in the current week in the particular region where the borrower lives.
Case Region	The logarithm of one plus the C19 confirmed case number in the current week in every 10,000 people in the particular region where the borrower lives.
Death Nation	The logarithm of 1 plus the number of deaths caused by C19 in the current week in the particular region where the borrower who created the loan originates.
Death Region	The logarithm of 1 plus the number of C19 deaths cases in the current week in every 10,000 people in the particular region where the borrower originates.
Most Infected Region	A dummy variable measures the origination location loan, which equals to 1 if the loan is created by a borrower lives in the regions with high infections or 0 otherwise.
Default	A dummy variable measures the outcome of loan, which equals to 1 if the loan is recorded as default or 0 otherwise.
Interest Rate	The interest rate (in percentage) for a particular P2P loan.
Maturity	The months of maturity of a P2P loan listed on the secondary market.
Share. Unpaid	The ratio of the note's principal to the original principal when the note is listed in the P2P secondary market.

Table TA2.10: Region- and country-specific C19 information flows.

	Infections			Deaths	
	Case Region	Case Nation		Death Region	Death Nation
Case Region	1.0000		Death Region	1.0000	
Case Nation	0.4455***	1.0000	Death Nation	0.4535***	1.0000

This table represents the correlation between country- and region-specific information flows. *Death Region* and *Case Region* present the logarithm of number of weekly death cases and confirmed cases in a particular region of Spain, respectively. *Death Nation* and *Case Nation* present the logarithm of weekly number of death cases and confirmed cases in Spain, respectively. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table TA2.11: Confirmed cases and deaths information flows.

	Country-wide			Region-wide	
	Death Nation	Case Nation		Death Region	Case Region
Death Nation	1.0000		Death Region	1.0000	
Case Nation	0.9235***	1.0000	Case Region	0.8971***	1.0000

This table represents the correlation between death and infection information flows. *Death Region* and *Case Region* present the logarithm of number of weekly death cases and confirmed cases in a particular region of Spain, respectively. *Death Nation* and *Case Nation* present the logarithm of weekly number of death cases and confirmed cases in Spain, respectively. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table TA2.12: Descriptive statistics for C19 related information

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	p25	p50	p75	Std	Obs.
Nation Trends	2.629	0.000	0.857	3.000	5.695	342
Region Trends	20.565	8.000	16.000	30.571	17.856	342
Nation News	3.646	0.000	0.000	4.000	7.082	342
Region News	86.056	31.000	82.000	123.000	62.355	342
Nation Mobility	74.536	23.359	63.006	120.885	49.014	342
Region Mobility	65.715	17.420	45.301	118.620	50.158	342

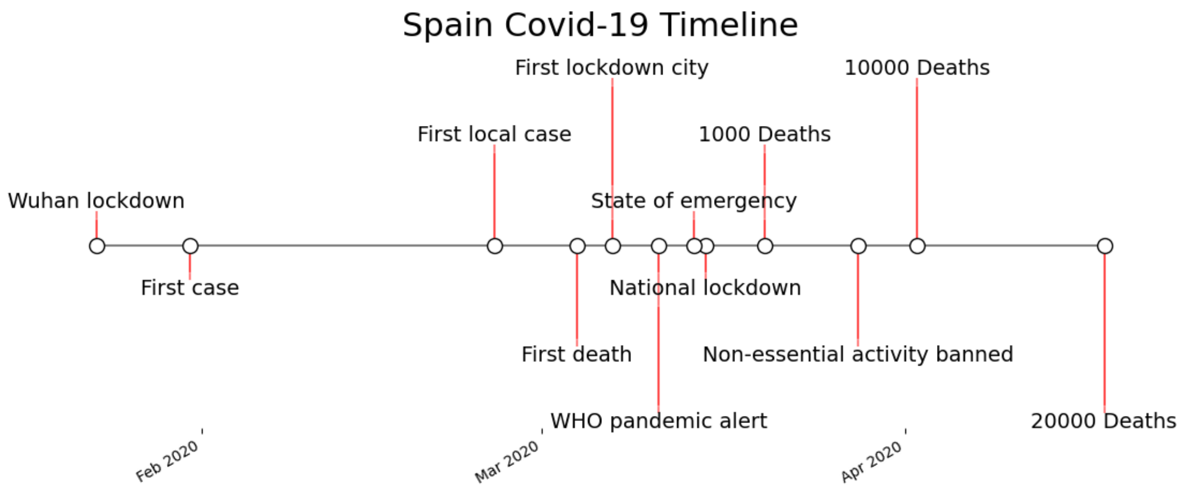
Note: This table reports the descriptive statistics for media attention and lockdown proxies used in estimations. Consistent to the loan-week panel, all variables are aggerated on week level.

Table TA2.113: Robustness check for fixed effect regressions

	(1)	(2)	(3)
Panel A: investor reaction on infection-related information			
	No. of Notes	**Discount**	**Share. of Success**
Outstanding Principal	0.1721	-23.0556***	37.2156***
	(0.1552)	(2.2732)	(3.6095)
No. Loans	0.1703***	4.2218***	-2.4517***
	(0.0083)	(0.1216)	(0.1931)
Loan Age	-0.3154***	4.7911***	-20.6770***
	(0.0320)	(0.4690)	(0.7447)
Case Region	0.0022	-0.2554***	0.7279***
	(0.0027)	(0.0401)	(0.0637)
Case Nation	0.0018	-1.0749***	3.3729***
	(0.0020)	(0.0291)	(0.0462)
Observations	75,804	75,804	75,804
R-squared	0.2131	0.5077	0.4135
Panel B: investor reaction on death-related information			
Outstanding Principal	0.1584	-21.2374***	32.2361***
	(0.1584)	(2.3203)	(3.7374)
No. Loans	0.1711***	3.9488***	-1.0307***
	(0.0085)	(0.1239)	(0.1995)
Loan Age	-0.3315***	5.9099***	-23.6831***
	(0.0333)	(0.4879)	(0.7858)
Death Region	-0.0019	-0.0468	-0.1232
	(0.0035)	(0.0506)	(0.0815)
Death Nation	0.0042*	-1.3030***	4.1157***
	(0.0022)	(0.0318)	(0.0512)
Observations	75,804	75,804	75,804
R-squared	0.2138	0.5107	0.4063

This table present the results for model (1) with *No. of Notes*, *Discount* and *Share. of Success* as the dependent variable in Panels A and B, respectively. The dependent variables and independent variables are consistent with the regressions in Table 2.3. In all estimations, only loan fixed effect is included but not reported, month fixed effect and region fixed effect are excluded. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

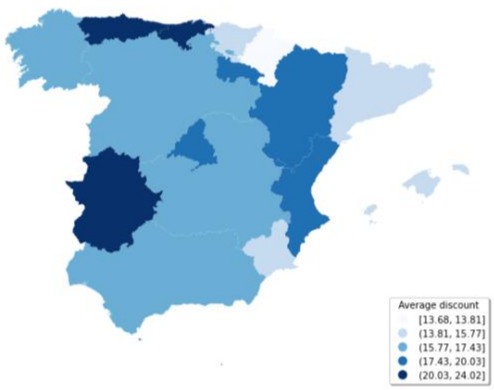
Figure FA2.3: The timeline of COVID-19 outbreaks in Spain



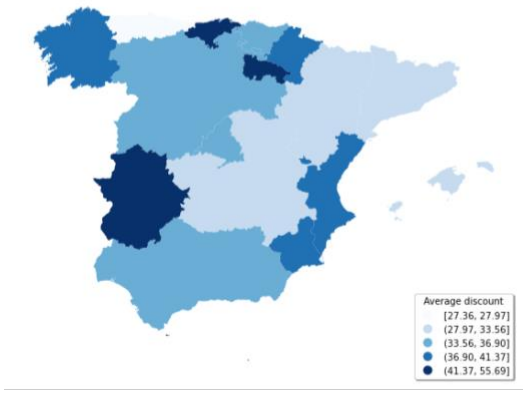
This figure shows the timeline of Spanish C19 pandemic. The first case in Spain is confirmed on 1 February 2020. The first local transaction case is confirmed in late February 2020. The community transmission exposes soon. Spain becomes the second epicentre in continental Europe since early-March. Spanish government announces national emergency status and lockdown restrictions on 14 and 15 March. The restricted lockdown starts to be lifted from 13 April 2020. On 28 April, government announces to ease most of lockdown restrictions from 2 May 2020.

Figure FA2.4: Descriptive statistics on Spanish region level

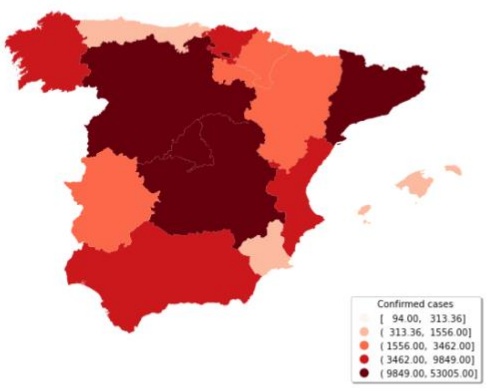
Panel A: Average discount in February 2020



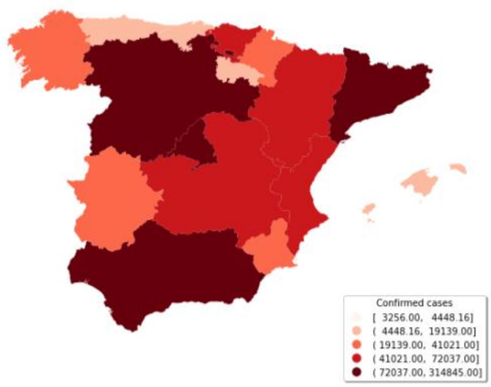
Panel B: Average discount in May 2020



Panel C: Confirmed cases in February 2020

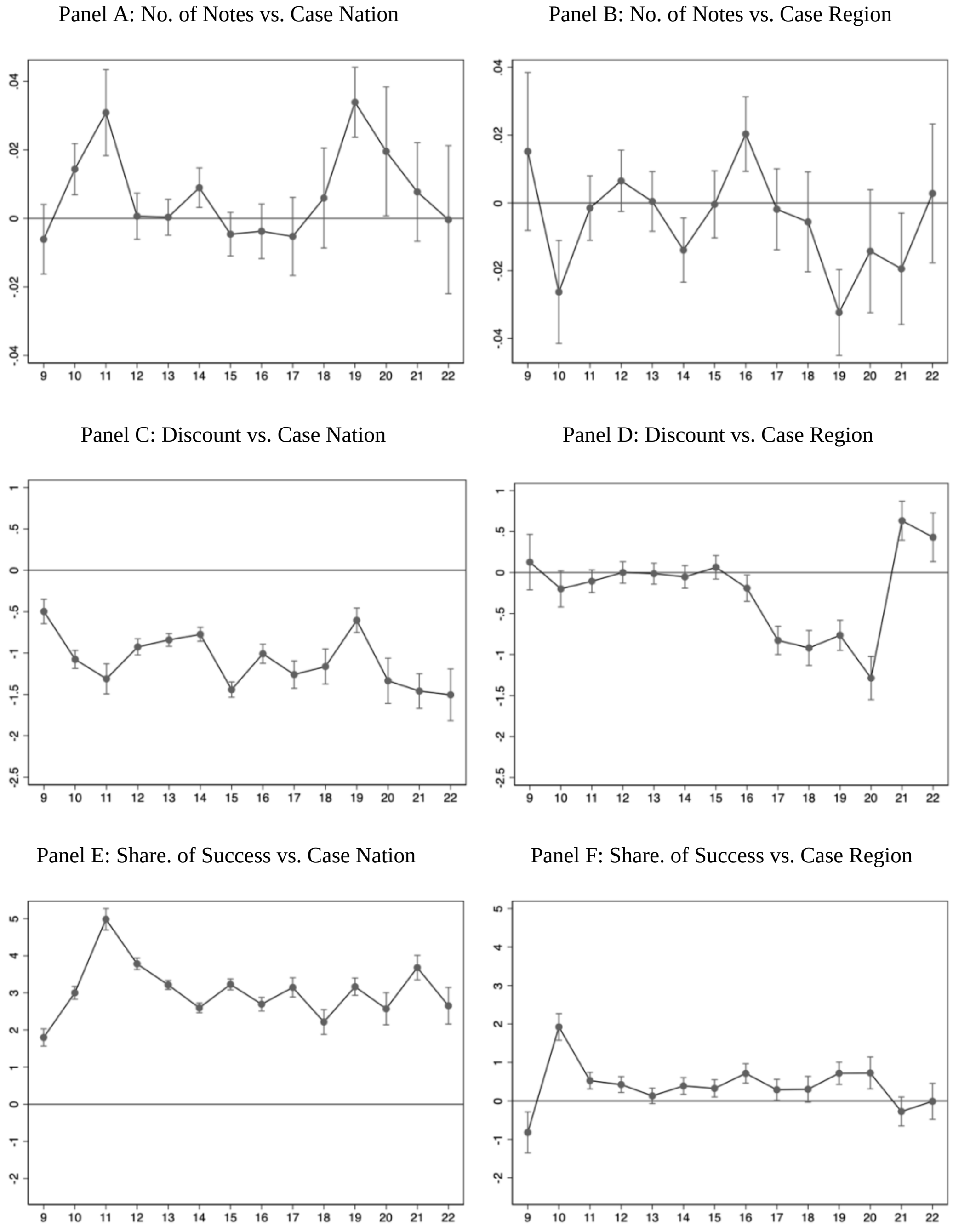


Panel D: Confirmed cases in May 2020



Note: this is figure represents the variations of several indicators among Spanish regions. Panel A and B represents the average price of notes (discount) among each region in March 2020 and May 2020, respectively. Panel C and D represents the number of confirmed cases among each region in March 2020 and May 2020, respectively.

Figure FA2.5: The revolution of the COVID-19 effects on asset pricing dynamics



This figure shows the dynamics of the C19 effect over the pandemic period. The dependent variables in all regressions are consistent with the settings in Table 2.3. The independent variables displayed in each graph are interacting cases with week indicator. The X-axis represents *Week*, the week dummy in 2020, the Y-axis represents the size of the coefficient. All the nodes represent the coefficient of the interaction between C19 cases and week dummies. Panel A represents the coefficient of *Case Nation* * *Week* on the *No. of Notes*. Panel B represents the coefficient of *Case Region* * *Week* on the *No. of Notes*. Panel C represents the coefficient of *Case Nation* * *Week* on the *Discount*. Panel D represents the coefficient of *Case Region* * *Week* on the *Discount*. Panel E represents the coefficient of *Case Nation* * *Week* on the *Share. of Success*. Panel F represents the coefficient of *Case Region* * *Week* on the *Share. of Success*.

Chapter 3: Investor Distraction during Holidays: Evidence from P2P platforms

3.1 Introduction

The phenomenon of investor behaviour around public holidays has been widely documented in stock markets (such as Ariel, 1990; Meneu and Pardo, 2003; Kudryavtsev, 2018) and futures markets (Fabozzi et al., 1994; Ryu and Yu, 2021). Prior studies suggest that investor attention might be distracted around public holidays (e.g., Luboshitzky and Gaber, 2001; Dellavigna and Pollet, 2009). Specifically, the celebration of holiday drives attention away from the financing issues (e.g., Pantzalis and Ucar, 2014). However, the research on whether investors keep trading pace in holiday dates is still limited as most of markets close during public holidays. Even the 24/7 foreign exchange market closes during public holidays. Equipped with unique dataset from international peer-to-peer (P2P) lending platforms, this study examines whether there is a holiday effect in P2P two-sided market that never closes.

Matching investors and borrowers without intermediaries, P2P lending market is unique for exploiting our research questions. P2P platforms allow trading throughout all day, and it opens in all calendar dates unless there is technical or policy issues (Bondora.com, 2016). Investors benefit from the simplified procedures, cost-efficient transaction process and information transparency compared to traditional financial markets (Collier and Hampshire, 2010). Yet, they are also composed by investors who are not well-equipped to cope with the risks associated with lending in risky markets (Lee & Lee, 2012). These features allow us to investigate instant investor behaviour dynamics in any particular date and hour throughout a long-term period.

To examine whether the P2P investors are distracted during public holidays, we collect data from *Renrendai* and *Bondora*, two leading P2P lending platforms in China and Europe. *Renrendai* provides flexible loan service with both borrower and investor in China: borrowers apply loans by filling in personal identity, and lenders bid to the unsecured loans by manual bidding or automatic tools (Teply and Polena, 2020). The loan data contains borrower characteristics including socio-demographic (e.g., ID number) and financial information (e.g., income), each loan listing contains the history of all biddings. Similarly, The *Bondora.com* facilitates funding to individuals located in Spain, Estonia, Finland and Slovakia, and it attracts investors from pan-European countries (Gavurova et al., 2018). *Bondora* loan service allows lenders to directly invest loans applied by borrowers. *Bondora* also operates secondary market in which the investors are allowed to trade their assets (notes) which are shares of loans originated from primary market. The transaction record and loan repayment history are visible to investors; hence one can observe large-scale information to facilitate their decisions.

We first illustrate how the public holiday increases the investor distraction. Similar to prior studies such as Zhang et al (2021), we use the investor decision time to proxy the investors distraction. Our estimations based on Renrendai datasets suggest that, investors tend to spend longer time to make purchase decisions during public holidays. For instance, the average decision time for an Renrendai investor increases 4.3 hours during holidays. The results are quantitively similar after controlling the loan size and entire fundraising progress. When we turn to the Bondora secondary market, we proxy the investor distraction by using seller's trading volume. Indeed, the trading volume measured by the number of notes of a P2P loan decreases by 1.7. The average time on market of each asset in Bondora secondary market in holidays increases by 1.3 hours. These findings suggest that both sellers and buyers are more distracted to make decisions during public holidays.

This study extends the baseline estimation by exploiting the drifts in investment performance and mismatched asset valuation. Our estimations suggest that the quality of investor decision during holidays is significantly lower than normal calendar periods. First, our estimate shows the return rate of fundraising decreases by 0.4 percent points in holidays. Also, the Sharpe ratio is included to consider the risk terms. The result suggests the Sharpe ratio declines by 0.71 percent points in holidays. The significant drop in investment performance indicates that investors cannot maintain their general performance during holidays. When it comes to the secondary market, the price of loan holdings is asked by the sellers, buyers manually observe the listings and decide whether to purchase. Therefore, the mismatched belief would arise the issue of asset mispricings. Our estimates based on the secondary transaction dataset suggests that, the mispricing of holiday trading is increased compared to normal trading dates. That is, investors are more carelessness during the public holidays, consequently, the mismatched asset valuation between sellers and buyers is enlarged.

Established these insights into the holiday distraction, we further consider the role of investor familiarity on the holiday trading effect. We exploit the interrelation between investor's holiday distraction and level of experience on the market. For Renrendai investors who have experience on the market no more than 1 year, although the decision speed of holiday trading is delayed, they still maintain the quality of investments. During the second year, inattention is even more intensive as the decision speed further delays and the performance significantly declines. Interestingly, investors equipped with more than 2 years experience only show mild holiday distraction, whereases their performance is still inferior. Overall, the experienced investors are most likely to make poor decision under holiday distraction.

This paper builds on literature focuses on the literature focuses on the role of holiday factors in investor decision. There have been studies on the holiday effects on stock market (e.g., Lakonishok and Smidt 1988; Pantzalis and Ucar 2014), foreign exchange market (Carchano and Pardo, 2015) and futures market (Lahav, Shavit and Benzion, 2016). Previous studies focus on the normal trading days before the upcoming holidays (e.g., Cadsby and Ratner, 1992; Gama and Vieira, 2013). The issue of estimating the investor attention in holiday trading days is still limited. Furthermore, there has been literature investigates the investor attention during special events overlap with trading days (e.g., Fang et al., 2018; Qadan and Kliger, 2016), but the FinTech innovation provides a marketplace in which individuals seek profits throughout all day and all year. Thus, the research on the holiday trading of P2P investor has not been investigated yet. Indeed, this analysis differs in turning attention to the investor behaviour in holiday trading days in the P2P markets.

This paper also adds to the behavioural economics literature shedding light on the investor inattention. Recent literature suggests that investor attention might be occupied by events such as Friday (Dellavigna and Pollet, 2009), religious holiday (Jacobs and Weber, 2010) and news explosion (Hirschleifer et al., 2009). Specifically, the religious holiday would trigger the movements of investor moods[44]. Benefited the results from EU environment (equipped with religious holidays) and China market (equipped with non-religious holidays), we document that public holiday drives investors to exit the financing activity, consequently the investment performance dramatically declines.

Our study further contributes to the literature on the heuristic bias of investor behaviour. There has been evidence that investors could be affected by heuristic bias such as herding (e.g., Zhang et al., 2012), overconfidence (Adebambo and Yan, 2018) and information underreaction (Gietzmann et al., 2021). However, whether the level of inattention related to holiday varies from the level of investor experience is still unknown. This study extends the understanding of investor heuristic bias by exploring whether the familiarity to the market would enhance the holiday distraction. Indeed, the holiday trading exhibits a learning tendency as the performance of experienced investors are more likely to be affected by holiday distraction.

We construct the paper as follows. Section 2 provides information about the backgrounds of two P2P lending platforms and the public holiday settings. Section 3 represents the data and the associated descriptive statistics. Section 4 presents our methodology and the empirical model. Section 5 presents the results. The last section concludes the paper.

3.2 Public holiday

In this study we select two P2P lending platforms based on continental Europe and China, two regions differ from economy, culture, society and religion. The public holiday setting of China is extracted from the public holiday calendar issued by General

[44] For instance, the Jewish holy holidays could affect the trading strategies in Dow Jones stocks (Yaktrakis and Williams, 2010).

Office of the State Council of PRC[45]. During 2010 to 2018, there are several main national public holidays: Lunar New Year, Labor's Day, National Day, Dragon Boat Festival, Tomb Sweeping Day. The Labor's Day and National Day are fixed, whereas rest of holidays are scheduled based on the Chinese Lunar Calendar. We therefore manually locate these holiday dates and its vacation dates. Those public holidays are also widely employed in empirical studies focus on the holiday effect on Chinese stock markets (e.g., Lu et al., 2016; Yuan and Gupta, 2014).

The settings of European holidays are even more sophisticated than Chinese holidays. Prior works such as Batrinca et al (2018) have investigated the cross-market effect of public holidays among pan-EU stock markets. Operating in all EU countries, the Bondora platform attract P2P investors across pan-European area. However, the settings of public holidays in each country may differs from others. Hence, we explore the public holiday calendars from EU countries and only includes several the most commonly consumed public holidays, such as Christmas, Easter, Labour's Day, Assumption Day and All Saints Day. We choose public holidays celebrated in at least 14 EU countries, which is more than half EU members[46]. Also, these holidays are also the most-employed public holidays for empirical analyses which investigate the European stock market response to the public holidays (See at Dodd and Gakhovich, 2011).

3.3 Data

To pursue the investigation, we employ data from Renrendai.com and Bondora.com, two leading P2P lending platforms in China and Europe, respectively. In this section we will discuss the data collection and process.

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[45] For instance, the arrangement of 2021 public holidays is extracted from the governmental document issued by General Office of the State Council of People's Republic of China. Website: http://www.gov.cn/zhengce/content/2020-11/25/content_5564127.htm

[46] The arrangements of public holidays across EU countries is collected from Q++Studio, a professional calendar service provider. For instance, the public holiday calendar in 2021 is extracted from the following website: https://www.qppstudio.net/publicholidays2021/eu.htm

3.3.1 Renrendai primary data

We employ data from Renrendai.com between the period from October 2010 to October 2018. It is worth noting that, the Renrendai only operates the primary loan market, the loan holdings are not allowed to be transferred in the Renrendai platform. The Renrendai data is collected from two sources. First, we collect loan information about loan and borrower characteristics. Second, for each P2 loan, we capture the bidding records and identify the bidder for each bidding. Therefore, each bidding record is specifically linked to a single lender ID. These two resources are assembled by matching the specific loan ID and lender ID. Consequently, each investor (lender) observation is equipped with its historical bidding records, each bidding is labelled with the lender ID, bidding time, bidding amount and loan listing information such as annual interest rate, credit ranking, requested loan amount, listing time, maturity, and duration. Renrendai publishes borrower characteristics such as borrower ID, monthly income, borrower age, employment situation, residence location, educational level, immovable property ownership, and credit history on the platform. Finally, for each bidding, we construct a dummy variable to depict the hour of day and day of week. Finally, our dataset is constructed on the investor-bid basis. The bidding of each investor is structured based on the bidding time.

Table 3.1 shows the loan-level descriptive statistics on several parameters of investor bidding behaviour during holiday and non-holiday period. The borrowing cost for borrowers is measured by the *Interest Rate*, the asked interest rate given by the borrowers. The *Interest Rate* is 12.2 percent points at non-holidays, however, in holidays borrowers have to pay the Interest Rate at 14.1 percent points. The investor decision time for an investor is measured by *Time on Market,* the time gap from the loan is posted to a particular investor bid to it. The average *Time on Market* on a loan listing is approximately 4.6 hours during normal calendar days. This number increases to 9.5 hours during public holidays. The market level investor is proxied by *Market Volume,* the logarithm of 1 plus the number of investors bid to a particular loan. The average *Market Volume* is 5.5 during non-holiday period, however this number decreases to 5.2 during holidays. Finally, the *Sharpe Ratio* during normal dates is 0.6, but this parameter decreases to 0.5 during public holidays. These features suggest that, during public holidays, the market volume shrinks and the active investors on the market drops. Further, investor invest much slower during public holidays than the normal period, and their investment performance is lower than normal calendar days.

3.3.2 Bondora secondary market data

We collect secondary loan transaction data from publicly available data published by Bondora.com. The dataset is obtained from three resources: (1) loan information extracted from primary loan service, which records public information for all loans from 2013 to 2021; (2) secondary market dataset, which records all secondary market transactions from 1 January 2016 to 31 Dec 2021; (3) historical repayment recordings, which contains all repayments of granted loans covers the period from 2013 to 2020.

We combine these datasets based on the unique loan identifier. Then, the dataset is clean by the following procedures: First, Bondora mainly service for loans with long-term maturity, therefore all loans created with less than three years maturity are excluded. Second, we aim to eliminate the effects of outliers with extreme values, therefore observations with the asked price (discount rate) are dropped at the top 1% level of distribution. After eliminating the outliers, each P2P loan in the sample is equipped with the unique secondary market transaction, as well as the repayment recordings. In result, the dataset includes 2,447,369 loan-day observations pertaining to 65,373 loans and 26,613,042 notes and the sample spans from 1 January 2016 to 31 December 2021.

Table 3.2 presents the note-level descriptive statistics for 65,373 loans in the sample. Those loans pertain 27,883,975 note transactions. The sample contains loans traded in secondary market during the period from 1 January 2016 to 31 December 2022. In this chapter, we focus on a particular research question that whether investor attention is distracted during public holidays. Therefore, we compare the notes listed during holidays and notes listed in normal calendar days. We first inspect the direct asset price proxy, *Discount*, the discount rate for the note asked by the sellers. It is observable that the average *Discount* is -7.5 percent points during normal trading days, whereas this number is -8.7 percentage points for notes being listed during public holidays. Then, we move to the measurement of investor decision time, the *Time on Market*, which is defined by the time gap from the note is listed to the note is purchased. During regular dates, it would take approximately 1.5 days for a note being successfully purchased. However, this progress requires about 1.7 days in public holidays. It is worth to note that, the time of decision only considers the notes that are successfully sold, notes cannot be taken in 30 days would be tagged as failed, therefore those notes have the same time scale on the market. Additionally, we employ *Market Volume*, defined by number of notes listed on the market in a particular day, to proxy the trading volume on the market level. The market volume in normal days is about 25,403, whereas this number is only 21,109 during holidays. The Success is defined by the Overall, the comparison between holiday and non-holiday trading activity indicates that, sellers list fewer assets at lower prices during holidays, and buyers spend longer time to make decisions.

3.4 Econometrics Specification

3.4.1 Renrendai investor behaviour

The very first key research question of this analysis is to figure out whether the public holidays affect investor attention. To proxy the investor attention on the P2P market, we use the decision time of investors, *Decision Time*, which is defined by the time period from the loan is posted on the market to a particular investor bid to the P2P loan. For instance, if a P2P loan is posted at 12:00, and an investor *i* bids to this loan at 14:00, the Decision Time will be 2 hours. Then, to control the entire progress of the fundraising, we further introduce *Modified Time on Market*, which is defined by the rate of progress (measure by percent points). For instance, if an investor *i* bids to a P2P loan at 50 hours after its' posting, and this loan is fulfilled in 100 hours, the *Modified Time on Market* for investor *i* will be 50 percent points. Moreover, we use *Relative Position*, which is defined by the position of a particular bid out of all bids. Technically, if there are 100 bids for a P2P loan, and investor *i* make a bid as the 50th bids out of all bids, the *Relative Position* of investor will be 50 percent points.

To trace the investor behavioural dynamics, this estimation is built on the investor-bid level. Therefore, we run the regression below:

$$Investor\ Decision_{ij} = \alpha + \beta_1 \text{Holiday} + \beta_2 Z_{ij} + \varepsilon_{ij} + u_{ij} \qquad (3.1)$$

Where *i* represents the specific investor ID, and *j* denotes the rank of bid made by the investor *i*. Therefore, j = 10 means this bid is the 10th bid made by the investor. In particular, we examine the investor attention dynamics during public holidays, in this estimation *Investor Decision* vector captures three dependent variables including *Time on Market, Modified Time on Market* and *Relative Position*, respectively.

To quantify the effect of public holidays on the investor attention dynamics, we include the key independent variable *Holiday,* a dummy variable which equals to 1 if the bid is made during public holidays, otherwise it is equal to zero. The setting of the public holiday in mainland China involves all official public holidays at which people could take the off-work break. Indeed, the always-on P2P market allows us to get insight of the investor attention terms during this leisure time. The expectation is that investors take more time to make purchase or funding decisions during public holidays. Overall, this dummy variable provides a valuable opportunity to get an insight of the investor behavioural patterns when investors' attention is occupied by holiday celebration.

The vector *Z* includes several covariates. For instance, to include the effect of several borrower characteristics, we include *Risky*, a dummy variable which equals to 1 if the credit level of the P2P loan is identified as "High Risk".[47] The parameter reflects the liquidity situation of a borrower, *DTI-Ratio,* is also included as the ratio between the borrower's debt and income. The platform dynamics related to the market volume and peers behaviour are also captured by the *Log (Loans)* and *Log (Bidders)*. These two proxies record the market momentum when the investor make the bid, therefore we

[47] Renrendai classifies the credit level of a P2P loan into several categories, including "A, B, C, D, E, F and High Risk (HR)".

include them in the Z vector. In particular, *Log (Loans)* represents the logarithm of the number of total unique loans on the market when investor i bids to a P2P loan. *Log (Bidders)* is defined by the logarithm of the number of active bidder (investor) on the entire Renrendai market when investor i make the bid decision. This variable could be used to proxy the dynamics of peer's activity. We incorporate several types of fixed effects, such as investor fixed effect and month fixed effect to control the investor homogeneities and the seasonality throughout a calendar year. We also control the fixed effect related to the weekend activity, as the investors tend to have other routines during the weekends (see also Kim and Wie, 2018). In addition, the active trading time effect is also controlled. The estimation of Model (1) is based on the fixed effect estimator with robust standard errors.

In light of the abnormal investor decision time during the public holidays, we next examine whether investors underperform during public holidays. Previous studies, such as (Kudryavtsev, 2018), have documented the existence of abnormal stock return before and after public holidays. In this context, we investigate the connect between performance of investment and public holidays. In particular, we re-estimate Model (1) by replacing the dependent variable vector by *Invest Performance*, a vector which capture three variables: (1) *Invest Profit*, which is defined as the he logarithm of profit of investor i from a bid j. This variable provides a straightforward measurement to reflect the quality of an investment. (2) *Invest Return*, which is defined the rate of return in which an investor i could receive from the bid j. This factor takes the impact of the size (amount) of the investment into consideration. (3) *Sharpe Ratio*, which is defined by the ratio between the profit of an investment and the risk of the investment. The Sharpe ratio control the effect from both potential profit and possible loss, and it has been widely used in empirical studies to proxy the quality of an investment (e.g., Lewis et al., 2021).

3.4.2 Bondora investor behaviour

The rich data from two P2P platforms in two marketplaces with different culture background and holiday traditions gives us a valuable opportunity to examine whether the holiday-induced investor distraction echoes in different countries. In this section, we focus on the Bondora investor behaviour during public holidays.

Similar to the estimation based on Renrendai dataset, we first investigate the investor distraction factors in Bondora secondary market. Bondora secondary market allows loan holders sell their current asset in discount / par / premium value. In particular, several key parameters related to the investor behaviour, such as the timing of a loan being posted and removed, the asset price (measured by percent points), the outcome of the transaction (success or fail) and the previous repayment and default recording, are accessible to P2P investors. Therefore, the market dynamics could help us to have a better understanding about the investor decision making terms during public holidays.

Differs from the fundraising progress in Renrendai primary market, we use three factors to measure the investor distraction. First, we measure the extent to which investor are willing to post their asset on the market by *No. of Notes*, which is defined by the number of notes posted on the market for a P2P loan. This variable allows us to explore whether the sellers are willing to participant the investment activity. Also, this factor represents the liquidity of the secondary. Second, we use *Discount*, the average asset price asked by the sellers to measure the pricing behaviour of sellers. Indeed, this variable represents whether sellers are confident that their asset could be sold. The third measurement involves the speed of investment decision making by *Time on Market*, which is defined by the time period from the asset (note) being posted to the asset is purchased[48]. We select several major holidays which is widely celebrated in pan-European countries. Since the Bondora secondary transaction is rather active, the preliminary estimation is set on loan-daily level.[49] We therefore estimate the following regression:

$$Loan\ indicators_{i,t} = \alpha + \beta_1 \text{Holiday} + \beta_2 Z_{it} + \varepsilon_{it} + u_{it} \qquad (3.2)$$

[48] Since the Bondora buyers could rely on both manual decisions and self-setting portfolio managers, the decision time only include the purchase made by manual decisions.

[49] We also implement estimations on weekly level, the results are quantitively similar.

Where the *i* represent the unique loan number and *t* denotes the time indices.

The vector *Z* includes several covariates. For instance, to quantify the effect of loan maturity, we utilize *Loan Age*, which is defined as the logarithm of one plus the maturity of the loan. Loans approach maturity carry less risk as the borrowers have a proven repayment record. Hence, we expect the *Loan Age* to be positive for the average asset price. Similar to Morse (2015), we include *Outstanding Principal,* the share of outstanding principle in the current week out of the original principle to control the effect of stage of loan repayment process. The *Outstanding Principal* is expected to be positive for the average asset price, as the higher remaining principle normally means higher potential future repayment cash. To capture the effects of the overall market volume on the market, we follow Caglayan et al. (2021) and include *Market Volume*, which is the logarithm of one plus number of notes being listed on the market during the current week. Generally, a higher *Market Volume* posits a greater market volume that investor is more likely to ask higher price. We therefore expect *Market Volume* to be positively related to the asset pricing term. In addition, we incorporate two types of fixed effects, such as loan fixed effect and month fixed effect to control the loan characteristics and seasonality. The estimation of Model (1) is based on the fixed effect estimator with robust standard errors.

We then explore the quality of investment decision made during public holidays. Given the evidence of mispricing in P2P market (Caglayan et al., 2021), we capture the quality of investor decisions by proxy the mismatch between the seller's pricing and buyer's pricing behaviour. Similarly, the mispricing terms in financial markets have been examined by recent studies (e.g., Brown 2014; Miwa, 2016).

We first estimate the probability of the outcome (success or not) of each note listed on the market. Generally, a high-predicted probability of being sold might be considered as the seller's pricing is near the initial price where the asset should be (Walking, 1985). Whereas a low-predicted sold probability indicates the seller overvalue the price of asset. The probability of asset transaction outcomes (success = 1, fail = 0) is given by a machine learning framework, least absolute shrinkage and selection operator (LASSO). Technically, we use LASSO to predict an asset's sale outcome based on the information of the asset. We then compare the predicted probability of being sold of each note with its actual selling result. If a note with low-predicted probability is successfully sold, it means the buyer's pricing exceeds sellers pricing. In contrast, if a high-probability note is actually failed, we interpret the buyer's valuation is lower than seller's asked price. Therefore, we define the *Type 1 Mispricing* as a low-probability (lower than 0.25) asset successfully being sold. In contrast, *Type 2 Mispricing* suggests a high-likelihood (higher than 0.75) asset fails to be sold. To proxy investors' asset mispricing terms, we include *Share. Type 1 Mispricing*, defined by the share of Type 1 error of a P2P loan in the current week. Also, *Share. Type 2 Mispricing* is included to capture the share of Type 2 error of a specific loan.

3.5 Results

3.5.1 Investor decision time during public holidays

The very first research question of this study is to examine whether investor spend more time to make decisions during public holidays, compared to normal calendar days. The unique settings of P2P markets provide a chance to investigate this behavioural issue. In this context, we run regressions based on Model (1) and (2), respectively.

Table 3.3 reports the estimations on Model (1) using the Renrendai sample contains 8-year period from 2010 to 2018. The results suggests that, during public holidays, the investor tend to spend longer time to make funding decisions. In column (1), the public holiday dummy *Holiday* is positively associated to *Time on Market*, the investor decision time proxy. For instance, an investor would spend more 4.2 hours on an investment in public holidays compared to general normal calendar dates. Column (2) suggests that the *Holiday* is also positively associated to *Modified Time on Market*, the decision time normalized by the total hours of the entire fundraising progress. We further look at the holiday effect on *Relative Position*, the position of a bid out of all bids which a loan listing receives. In column (3), the public holiday dummy *Holiday* is positively related to the *Relative Position*, which suggest the investors react and make funding decisions slower during public holidays compared to the normal calendar days.

When we turn attention to the coefficients related to the control variables in Table 3.3, we observe that the significance associated with the remaining covariant is sensible. For instance, the size of requested loan amount would significantly increase the decision time for an investor, it is in line with our expectation as a larger loan would naturally increase the time on market. Also, the proxy for the peer pressure, *Log (Bidders)*, is negatively associated to the decision time. It is meaningful as more logged investors would significantly enforce a single investor to make fast decisions. It is interesting that Log (Loans) is almost insignificant to the decision time proxies, this finding might be explained that investors have only limited attention to the market, therefore the number of loans cannot drive a single investor in the decision time.

In Table 3.4, we investigate the Bondora investor attention throughout both sellers and buyers perspectives. First, we assess the sellers activity via the market liquidity. In column (1), the public holiday dummy is negatively related to the market liquidity proxy *No. of Notes*. For example, a P2P loan has 1.69 notes normalized by the number of listed dates less than the periods of normal calendar dates. This finding suggests that the sellers would list less asset on the market during public holidays. In column (2) we use *Discount* to measure the sellers' valuation on the notes of P2P loans. In particular, the *Holiday* dummy is negatively associated to the *Discount* as the average price of assets is 2.0 percent points lower than the price during normal calendar days. This coefficient indicates sellers tend to reduce the valuation on their loan holdings.

We next explore the Bondora buyers' reaction to the public holidays. In column (3), *Time on Market* is the direct proxy to measure the time period from a note being listed to the note being purchased. Therefore, this indicator is a key to understand the buyers' decision speed. Specifically, during the public holidays, the buyers are likely to spend more 2.3 hours to make the purchase decision compared to the regular periods. This evidence further suggests the importance of the timing of listing. In light that buyers' attention is likely to be distracted by the public holidays, the notes posted early will be covered by the new-coming selling requests, in a word, posting loan holdings during public holidays seems not to be an optimal decision for sellers who intend to get rid of their loan holdings.

The results of Table 3.3,Table 3.4 demonstrate that, the speed of decision-making progress is significantly slower during public holidays. First, in Renrendai fundraising market, the investor bids to loan listings significantly take longer time since the listing is posted on the market. After controlling the total hour used in the entire fundraising progress, this finding is consistent. Second, in Bondora secondary market, both sellers and buyers show higher degree of inattention during holidays. The sellers list less loan shares and reduce the price of their current assets. The listed loan holdings will stay longer time on market to be picked by the buyers.

These two signals, subsequently, could lead to one possible interpretation that, if a financial market is still open during the public holidays, the investors are still willing to log into the market and invest/trade, however, they are more distracted and react slower to the market information. This phenomenon is consistent in different cultural backgrounds and business models. Previously, Chong et al (2005) provide the international evidence on holiday effect in US, UK and HK stock markets. Therefore, we may say, the inattention during holidays might be driven by the specialized holiday rotations. The inattention during holidays might be explained by several possible behavioural terms, such as the religious activity, vacation travelling and holiday celebrations.

Although we have no assess to investors' timetable for their daily routine, we could still attempt to explain this phenomenon throughout the comparison between two totally different P2P environment. One could possibly interpret that, the limited attention to handle the investment on P2P market is associated to the holiday calendar, therefore the investors are occupied by the celebration issues of holidays. As a result, the primary loan applications, and the secondary loan holdings, will take longer time to wait for the manual picking-up. The depressed investor attention in public holidays leads to one possible problem, as investors are more distracted, whether they can maintain their decision quality level as usual during the public holidays? In the next subsection, we will assess the investor performance factors during public holidays.

3.5.2 Investor decision quality during public holidays

In the previous section, we find the evidence that the investor is more distracted during public holidays. In this section, we investigate a following critical question, that is, whether their decisions made during public holidays underperform compared to the normal calendar periods.

Table 3.5 reports the estimations of Model (1) based on Renrendai investor bidding recordings. We first measure the investment performance by using the *Invest Profit*, the investment profit of each bidding. This variable provides a direct proxy which represents the future profit comes from the interest repayment. In column (1), the public holiday dummy *Holiday*, is negatively associated to the *Invest Profit*, which suggests that, the profit comes from the bidding decision made during public holidays is likely to be lower than the investment during normal calendar dates. Next, we consider the effect of the amount of each bidding. Normally, a larger size bidding is expected to generate higher profit. Therefore, we use *Invest Return*, the rate of return to further reflect the quality of each bidding. Subsequently, we observe the *Holiday* dummy is significantly negative to the return rate of bids. This finding further confirms that, after eliminating the size of bidding, the performance of investment is still lower during public holidays.

So far, we have measured the investment performance via the return perspective. Further, we attempt to include the risk terms to have a more balanced understanding on the investment performance. In this context, we include the *Sharpe Ratio*, to involve both return and risk factors. In column (3), the regression based on model (2) indicates that the *Holiday* is negatively related to the Sharpe ratio factor. This evidence suggests that, after including the risky factors, the investment performance during holidays is still lower than normal calendar periods. It provides a balanced measurement to consider the investment quality via both return and potential loss propensities.

In light of previous literature investigates the mismatched beliefs between sellers and buyers on asset valuation, the unique dataset of Bondora secondary market allow us to assess the investor decision quality by proxy the mismatch between sellers and buyers on the asset pricing. The results in Table 3.6 suggest that the mismatch between sellers and buyers seems to be expanded during public holidays. In column (1), the *Holiday* is positively related to the *Share. Type 1 Mispricing*. In particular, the mismatched asset valuation captured by *Type 1 error* increases 2.2 percent points during public holidays. In this context, this result suggests that more low-quality loans have been accepted during public holidays. When it comes to the type 2 error in column (2), the *Holiday* is also positively significant to the *Share. Type 2 Mispricing*. This coefficient indicates that loans posted public holidays are more likely to face up with this situation: the loan holding seems to be properly priced, however this holding is overlooked or missed after its posting. After including type 1 and 2 error, the *Holiday* is still positively associated to the *Share. Mispricing*, which is consistent with the results in column (1) and (2).

The results reported in Table 3.6 indicate that the public holiday create a predicament in which sellers and buyers generate more-divergent asset valuation during public holidays. The mismatch could be observed throughout two errors. First, the increasing *type 1 error* might lead to one interpretation that the buyers do not pay the equal attention or focus on the market as usual days, therefore they would pick more low-quality loans during public holidays. Second, the increasing *type 2 error* could be interpreted as the distracted holiday buyers are more likely to miss or overlook those loans which are very likely to be purchased in normal calendar periods. Overall, the estimation on investor mispricing behaviour during holidays provides evidence that the investors are more likely to make sub-optimal purchase decisions, as well as non-purchase ignoring during holidays.

Overall, the investment quality estimations based on both Renrendai and Bondora marketplaces provide consistent evidence that, investors during public holidays are more likely to make sub-optimal decisions. In Renrendai primary loan market, the investors keep trading during public holidays, however, the performance of those holiday trading is significantly lower than the normal level where it should be. In Bondora secondary market, the sellers and buyers in the market are also facing with this problem. The mismatched belief expands during holidays, suggesting that both sellers and buyers are affected by the holiday-induced inattention and then their judgement on asset valuation is more likely to be biased or improper.

It is worth to note that, there has been debating on the decision time and decision quality. Some papers suggest that the individuals might make quick but suboptimal decisions under peer pressure. Therefore, it might be better to use "wait and see" strategy. For instance, Zhang et al., (2021) document that the investors should wait others invest and bid to the loans which have been nearly-funded. In other word, if they spend longer time on the market, observe and think, the performance should be better. However, this chapter finds that the holiday effect induces investors not only react slower, but also perform lower. This conflict is essential to the key argument of this paper. It indicates the slow reaction during public holidays is not because the investors spend longer time (or more careful), indeed, the under-performance during public holidays is because investors are more careless and distracted.

3.5.3 Investor experience and holiday effect

Table 3.7 presents the estimations when we split the sample in light of the experience of investors on the market. In particular, column (1)-(3) capture the holiday trading of investors who have experience on the market less than 1 year, 1year to 2 years, more than 2 years. It is interesting that, the investors holiday trading behaviour varies from how long they have been stay on the market, which suggests that the holiday distraction exhibits learning heuristics features.

Panel A of Table 3.7 reports the estimation of decision time on subsamples based on investor experience on the market. In column (1), investors with experience less than 1 year spend longer time on the platform to make funding decision during public holidays. In particular, the decision time for an investor might increase 6 hours during holidays. When the investors are getting more familiar with the system, this effect is even larger as the 1-2 year-experienced investors might use more 8 hours to make investment. This phenomenon slightly releases when the investor stays in the market for over 2 years, as the average holiday decision time is 2 hours above the normal days. These findings indicate that, investors are distracted by the holiday effect since they start to invest in the market, this effect gradually increases during their second year, and after 2 years on the market, investors are getting used to handle the investing issue during holidays.

When we observe the Panel B, Table 3.7, we observe that, the coefficient of holiday dummy is still negative in column (1), but it is insignificant. This result suggests that, investors join in this market no more than 1 year seems not to underperform during holidays. However, in column (2), the investment quality significantly drops during holidays during the investor's second-year on the platform, the *Sharpe Ratio* of a bidding made during holiday significantly drops 8.8% compared to the decisions come from non-holiday periods. In column (3), this behavioural pattern for investors' investment made since their third-year on the platform is generally in line with the finding on their second-year.

The estimation on investor's experience suggests that the holiday effect on individual investors may drive their decisions as a heuristic term. In the first year, although the attention of investors is occupied, individuals are still "hardworking" as their performance of holiday trading keeps. However, in the second year on the market, investors are more easily to be distracted and make more sub-optimal biddings. Finally, equipped with 2 years' experience on the market, investors can slightly speed up their decision-making progress, but their performance still struggles during holidays. Therefore, we could interpret from the behavioural movements, that is, rookie investors are still trying to maintain the level of their decision, thus, when they are slightly senior on this platform, the carefulness during holidays seems to slip away.

3.5.4 Does holiday effect exist on borrower loan level?

In light of the holiday effect on investor-bid level estimation, to ensure the robustness of estimations, we re-sample our dataset and estimate the standard model that has been widely employed in the existing literature for loan-level estimations. We start our investigation by estimating the following model to seek evidence of sequential correlation:

$$Loan\ Indicator_{it} = \alpha + \beta_1 \text{Holiday}(t \in Holiday) + \beta_2 Z_{it} + \varepsilon_{it} \qquad (3.3)$$

Where *Loan Indicator*$_{it}$ denotes the parameters relate to the P2P loan *i* applied in the date *t*. In particular, it contains several variables: the *Failed Outcome*, which is defined by the results of the fund-raising progress. If the loan listing is failed to receive requested amount, *Failed Outcome* is equal to 1, otherwise 0. *Fulfilled Hour* is defined by the number of hours from a P2P loan application is listed to the loan is fully funded.[50] Differs from the baseline estimations on investor level, this variable provides an aggregated insight of the time on market of the successfully funded loans. To measure the emergence of the loan for a borrower, the *Borrowing Cost* is also captured by the interest rate offered by the borrowers. This indicator helps us to understand to what extent the borrower needs this loan. It is worth to note that the difference between the model (3) to model (1) is the investor perspective: the investor level detailed we have investigated before now is embedded in the loans associated with its loan-specific information.

When we examine Table 3.8, we find that the *Holiday* is positively related to the failed fundraising outcome in column (1), which suggests that the loans created during public holidays are more likely to fail to raise requested funding amount. In column (2), the *Holiday* dummy is not significant to the *Fulfilled Hour*. This is sensible as we have the

[50] It is worth to note that, the time on market of unfunded loans would be tagged as 168 hours. Therefore, the loans sampled in this variable are those listings which have been successfully funded loans.

evidence that the automatic bidding service operates even faster during holidays under the smaller market volume. In column (3), the borrowing cost measured by the asked interest rate is significantly higher during holiday periods. This significance could be linked to one potential mechanism that the borrowers are equipped the expectation that borrowing in holidays are more difficult compared to the regular days. Overall, the aggregated loan level estimation provides further evidence that the holiday effect not only sheds light on investor community, but also exist in the loan-level.

3.5.5 Fake holidays: whether holiday effect is just a coincidence?

The baseline estimations provide evidence that investor is more distracted during public holidays and more likely to make unwise decisions. In this section, to eliminate the effect from particular calendar settings, we do a placebo estimation based on the fake holidays. Specifically, we set up fake holiday periods and create fake holiday dummies accordingly. For instance, for the Chinese Lunar New Year, we identify the same dates one-week ahead and one-week after periods as the fake Lunar New Year. The rest of holidays employed in the estimations are also re-set.

Table 3.9 reports the results of fake holiday estimation on both Renrendai and Bondora marketplaces. Generally, investors from both China and Europe do not really perform different in the fake holidays created intendedly. In column (1)-(2), the *Decision Time* and *Sharpe Ratio* of Renrendai investor are not affected by the *Fake Holiday* dummy. Similarly, the *Fake Holiday* dummy is not significantly related to the decision time proxy and mispricing term of Bondora investors. These signals further confirm that the coefficients of holiday dummies in our baseline estimation is not driven by coincidence or the seasonality among calendar months. Indeed, the holiday schedule plays profound implications to the abnormal inattention in holiday periods.

3.5.6 Post holidays: what happens after the holiday celebration?

Thus far, we have documented that the holiday effect would drive investors to delay their investing activity, and this effect is not raised by the random calendar selection. In this section, we provide a further insight on whether the holiday effect could be identified in the post-holiday periods. Technically, we define a three days' interval starts from the first working day post the public holiday. Then, we re-run the regressions based on model (3.1). Differs from the investors trade in stock market, the post-holiday effect in Renrendai P2P lending platform is rather moderate.

Table 3.10 reports the results of fake holiday estimation on Renrendai marketplace. Generally, P2P investors do not really perform different in the fake holidays created intendedly. In column (1), the *Time on Market* Renrendai investor is positively affected by the *Post Holiday* dummy. However, the effect of post-holiday dummy is much smaller than the *Holiday* dummy. Similarly, in column (2) and (3), the *Post Holiday* dummy is not significantly related to the Sharpe ratio proxy and investment return measurement of P2P investors. These signals suggest that the post-holiday dummies in our post-holiday effect estimation do not significantly affect the investment performance after the public holidays. This finding is not consistent to the previous studies focus on stock markets. Thus, it is sensible because the post-holiday effect of traditional financial market is raised by the holiday market closure. In contrast, there is no closing schedule for P2P lending platforms, therefore, the investors may still react and invest slower in the first a few days after the holiday dates. However, their performance generally returns to the normal levels.

3.6 Conclusion

Do public holidays affect P2P investor's decision-making? To illuminate this question, we evaluate the connect between the public holidays and investor decision-making factors. Using data extracted from two leading P2P lending platforms from continental Europe and mainland China, this study provides evidence that investor are more distracted by the holiday routines and tend to make worse decisions compared to the regular calendar dates.

This paper contributes to the empirical literature from three strands. First, this paper adds to the empirical finance literature on holiday effects by extending the holiday effect from pre- and post- spans to in-holiday periods. This work brings an early investigation on investor holiday trading in P2P markets. Second, this study adds to the literature by investigating the connect between individual investor attention and public holidays. Investors are more distracted to holiday trading, and their performance is significantly worse than what they behave during normal days. Third, this paper contributes to the behavioural finance studies by investigating the heuristic features of the holiday effect.

In this study, we find the following. First, we find the investors tend to spend longer time to make purchase decision during public holidays. That is, investor decision time during public holidays is significantly higher than normal calendar dates. This finding is consistent in both P2P market in China and in Europe. Second, we exploit whether the investor performance is affected by the holiday calendar. Individual P2P investors, both lenders in primary loan market and sellers/buyers in secondary market, are acting worse in holidays compared to their usual decision quality. Third, we examine the connect between holiday effect and the experience of investors on the P2P lending platform. The result suggests that the investors would be more likely affected when they stay more than 1 year in the market. The estimations on two different platforms based in two marketplaces with different cultural background and holiday settings generally echoes with each other, indicating the celebration of holiday might be responsible to the investor inattention during specific holidays.

This study provides several implications. First, the P2P lending market provides a more flexible and less-regulated marketplace for individuals. It opens throughout all dates in each year and never closes. However, this specific market setting seems to be not ideal for both investors and fund raisers. For those fund raisers, the loan application opened during public holidays might be overlooked or missed; for the investors, their "hardworking" investment do not bring more harvest, oppositely, investing in public holidays usually leads to worse returns. Second, it is a very interesting phenomenon that investors would still trade during public holidays. This maybe because the potential repayment is higher: In Renrendai platform, the borrowing cost is significantly higher during public holidays, which means the return rate asked by the borrower is higher. Although the risk of those loans is also higher, there are always investors being willing to chase the profit. In Bondora secondary market, the asked price of asset is also lower during public holidays, which also encourages investors to seek higher the potential return under higher risk. It is worth to note, although the asked return / asset price seems to be more attractive during public holidays, the actual profits (measured by Sharpe Ratio and mispricing terms) is lower during public holidays. We believe our work would benefit to future research on this behavioural pattern in FinTech industry.

Tables

Table 3.1: Descriptive statistics of Renrendai market

	Non-holidays			Holidays		
	Mean	Std.	Obs	Mean	Std.	Obs
Interest Rate	12.1752	2.6213	101,563	14.0556	2.6233	9,721
Time on Market	4.5995	8.7794	101,563	9.4760	17.3770	9,721
Volume	5.5246	1.6639	101,563	5.2346	1.5901	9,721
Sharpe Ratio	0.5603	0.3859	101,563	0.5483	0.1624	9,721

Note: This table reports the descriptive statistics for all loans which created from Renrendai primary market. *Interest Rate* represents the interest rate measured by percentage points proposed by the borrower of the loan. *Decision Time* represents the number of hours from a loan is posted to an investor bid to the loan. *Volume* represents the number of loans on the market when a particular loan is listed on the market. *Sharpe Ratio* represents the Sharpe ratio of the biddings which considers both return and risk of the bidding.

Table 3.2: descriptive statistics of Bondora secondary market

	Non-holidays			Holidays		
	Mean	Std.	Obs	Mean	Std.	Obs
Discount	-7.506	22.233	26,613,042	-8.542	22.833	1,270,933
Time on Market	1.500	6.904	14,255,793	1.736	7.278	723,568
Market Volume	25403.310	25412.920	26,613,042	21107.050	10500.820	1,270,933

Note: This table reports the descriptive statistics for all loans which created from Bondora secondary market. *Discount* represents the discount rate (in percentage) for the note asked by the sellers. *Time on Market* represents the time gap from the note is posted to the note is purchased. This variable only includes the notes being successfully sold. *Market Volume* proxies the number of notes posted in the same date in the secondary market.

Table 3.3: Renrendai investor decision time

	(1)	(2)	(3)
	Time on Market	**Modified Time on Market**	**Relative Position**
Holiday	4.2013***	3.6975***	0.5980***
	(0.0371)	(0.2216)	(0.1263)
Loan Amount	2.0179***	1.0953***	-1.1220***
	(0.0076)	(0.0637)	(0.0257)
Log (Bidders)	-0.9796***	-3.1021***	-0.4575***
	(0.0038)	(0.0260)	(0.0129)
Log (Loans)	-0.0001***	0.0003***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)
Risky	1.0959***	-1.3344***	-0.0541
	(0.0207)	(0.2167)	(0.0705)
DTI-Ratio	-0.1679***	-0.3319***	0.0090
	(0.0026)	(0.0133)	(0.0088)
Investor Fixed Effect	Yes	Yes	Yes
Weekend Fixed Effect	Yes	Yes	Yes
Active Time Fixed Effect	Yes	Yes	Yes
Observations	2,447,369	2,447,369	2,447,369
R-squared	0.2321	0.1293	0.1574

This table present the results for model (3.1) with *Time on Market*, *Modified Time on Market* and *Relative Position* as the dependent variables. *Time on Market* is the time gap between a loan is posted to the investor bids to the loan. *Modified Time on Market* is the time on market controlled by the total hours of entire fundraising progress of the loan which the investor bids to. *Relative Position* is the order of the investor bids controlled by the total number of bids which the loan receives from the entire fundraising progress. *Loan Amount* is the logarithm of 1 plus the requested of the P2P loan. *DTI-ratio* is the ratio between the debt and income of the borrower who creates the P2P loan. *Risky* is a dummy variable which is equal to 1 if the loan is identified as high-risk loan. *Log (Loans)* presents the logarithm of number of loan applications being listed on the market in the date. In all estimations, loan fixed effect, weekend fixed effect and active-time fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 3.4: Bondora sellers and buyers behaviour

	(1)	(2)	(3)
	No. Notes	**Discount**	**Time on Market**
Holiday	-1.6961***	-2.0408***	2.3450***
	(0.0248)	(0.0292)	(0.0713)
Outstanding Principles	6.9834***	-12.3382***	19.7766***
	(0.1017)	(0.1199)	(1.3804)
Loan Age	-2.0583***	5.2142***	5.2142***
	(0.0211)	(0.2206)	(0.2206)
Log (Loans)	10.6548***	-21.1701***	-21.1701***
	(0.0209)	(0.2438)	(0.2438)
Weekend fixed effect	Yes	Yes	Yes
Loan fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Observations	1,339,815	1,339,815	4,346,470
R-squared	0.5383	0.4527	0.0752

This table present the results for model (3.2) with *No. of Notes*, *Discount* and *Decision Time* as the dependent variable in Panels A and B, respectively. *No. of Notes* is the number of current listings in the current date. *Discount* is the average price of the notes of a given loan asked by sellers in the current date. *Decision Time* is the average time gap between a note is listed to it is purchased for a P2P loan in the current date. *Loan Age* is the logarithm of 1 plus the age of loans (in months). *Outstanding Principal* is the ratio of the outstanding principal in the given date to the original principal. *Log (Loans)* presents the logarithm of number of notes being listed on the market in the date. In all estimations, loan fixed effect, weekend fixed effect and year fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 3.5: Renrendai investor decision quality

	(1)	(2)	(3)
	Invest Profit	**Invest Return**	**Sharpe Ratio**
Holiday	-0.0303***	-0.3843***	-0.7203***
	(0.0004)	(0.0057)	(0.1815)
Loan Amount	0.0064***	0.0815***	0.6885***
	(0.0001)	(0.0012)	(0.0371)
Log (Bidders)	-0.0017***	-0.0264***	0.0121
	(0.0000)	(0.0006)	(0.0185)
Log (Loans)	0.0000***	0.0001***	0.0005***
	(0.0000)	(0.0000)	(0.0000)
Risky	0.0677***	0.9534***	-32.1337***
	(0.0002)	(0.0032)	(0.1013)
DTI-Ratio	-0.0086***	-0.1045***	1.2146***
	(0.0000)	(0.0004)	(0.0127)
Investor Fixed Effect	Yes	Yes	Yes
Weekend Fixed Effect	Yes	Yes	Yes
Active Time Fixed Effect	Yes	Yes	Yes
Observations	2,447,369	2,447,369	2,447,369
R-squared	0.5132	0.5098	0.1063

This table present the results for model (3.1) with *Invest Profit*, *Invest Return* and *Sharpe Ratio* as the dependent variables. *Invest Profit*, which is defined as the he logarithm of profit of the bid made by the investor. *Invest Return,* which is defined the rate of return in which an investor could receive from the bid. *Sharpe Ratio,* which is defined by the ratio between the profit of an investment and the risk of the investment. The independent variables remain the same setting as Table 2a. In all estimations, loan fixed effect, weekend fixed effect and active-time fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 3.6: Bondora investor decision quality

	(1)	(2)	(3)
	Share. Mispricing	**Share. Type 1 Mispricing**	**Share. Type 2 Mispricing**
Holiday	3.0247***	2.0430***	0.9816***
	(0.0290)	(0.0191)	(0.0223)
Outstanding Principles	11.9684***	-8.7077***	20.6761***
	(0.0832)	(0.0547)	(0.0638)
Loan Age	0.7066***	5.1808***	-4.4742***
	(0.0147)	(0.0097)	(0.0113)
Log (Loans)	-0.7915***	0.6587***	-1.4503***
	(0.0146)	(0.0096)	(0.0112)
Loan fixed effect	Yes	Yes	Yes
Weekend fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Observations	16,478,047	16,478,047	16,478,047
R-squared	0.0397	0.0691	0.0752

This table present the results for model (3.2) with *Share. error, Share. Type 1 error* and *Share. Type 2 error* as the dependent variables. The set of independent variables are the same as Table 3.4. In all estimations, loan fixed effect, weekend fixed effect and year fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 3.7: Renrendai investor experience and holiday effect

	< 1year	1 year to 2 years	2 years+
	(1)	(2)	(3)
Panel A: Decision Time and investor experience			
Holiday	6.3856***	8.5789***	1.3666***
	(0.0714)	(0.0746)	(0.0376)
Loan Amount	1.7000***	1.5472***	2.1979***
	(0.0104)	(0.0150)	(0.0164)
Log (Bidders)	-1.1018***	-0.6567***	-0.4923***
	(0.0069)	(0.0063)	(0.0048)
Log (Loans)	-0.0001***	-0.0001***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)
Risky	0.8893***	0.4473***	0.4802***
	(0.0279)	(0.0404)	(0.0528)
DTI-Ratio	0.0107***	0.0150***	-0.0250***
	(0.0012)	(0.0015)	(0.0014)
Observations	1,369,689	524,399	564,897
R-squared	0.2916	0.2597	0.1835
Panel B: Sharpe Ratio and investor experience			
Holiday	-0.4283	-0.8883**	-0.8786***
	(0.3721)	(0.4374)	(0.0561)
Loan Amount	0.3215***	0.9641***	1.6738***
	(0.0542)	(0.0882)	(0.0244)
Log (Bidders)	0.0432	-0.0034	0.0921***
	(0.0361)	(0.0372)	(0.0071)
Log (Loans)	0.0000	0.0001**	0.0002***
	(0.0000)	(0.0000)	(0.0000)
Risky	-30.2173***	-28.5561***	-27.1314***
	(0.1453)	(0.2368)	(0.0787)
DTI-Ratio	0.5448***	0.5839***	0.3627***
	(0.0060)	(0.0085)	(0.0020)
Observations	1,368,081	524,336	564,895
R-squared	0.1176	0.1156	0.4236

This table present the results for model (3.1) with *Sharpe Ratio* and *Time on Market* as the dependent variables in Panel A, B respectively. The independent variables remain the same setting as Table 3.3. In all estimations, loan fixed effect, weekend fixed effect and active-time fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 3.8: Holiday effect on loan cross-section level

	(1)	(2)	(3)
	Failed Outcome	**Fulfilled Hour**	**Borrowing Cost**
Holiday	0.0252***	-0.1931	0.2723***
	(0.0034)	(0.2147)	(0.0326)
Loan Amount	-0.0355***	-1.7341***	-0.2953***
	(0.0004)	(0.0301)	(0.0041)
Log (Bidders)	-0.0147***	-0.9744***	0.2939***
	(0.0009)	(0.0642)	(0.0086)
Log (Loans)	-0.1090***	-2.1675***	-0.4555***
	(0.0011)	(0.0838)	(0.0102)
Risky	0.0110***	0.2908***	0.2753***
	(0.0004)	(0.0236)	(0.0037)
DTI-Ratio	0.0252***	-0.1931	0.2723***
	(0.0034)	(0.2147)	(0.0326)
Weekend Fixed Effect	Yes	Yes	Yes
Active Time Fixed Effect	Yes	Yes	Yes
Observations	111,283	111,283	111,283
R-squared	0.4122	0.1046	0.2827

This table present the results for OLS regression with *Failed Outcome*, *Fulfilled Hour* and *Borrowing Cost* as the dependent variables. The independent variables remain the same setting as Table 3.3. In all estimations, loan fixed effect, weekend fixed effect and active-time fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 3.9: Robustness check: Fake Holidays

	(1)	(2)	(3)	(4)
	Decision Time	**Modified Time on Market**	**Invest Return**	**Sharpe Ratio**
Fake Holiday	-0.0501**	0.1559	0.0519***	0.0520
	(0.0222)	(0.1521)	(0.0032)	(0.0909)
Loan Amount	1.2640***	-1.1049***	-0.1089***	0.6213***
	(0.0084)	(0.0539)	(0.0012)	(0.0344)
Log (Bidders)	-1.1363***	-3.1192***	-0.0410***	-0.0010
	(0.0044)	(0.0257)	(0.0006)	(0.0181)
Log (Loans)	-0.0002***	0.0002***	0.0001***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Risky	2.1367***	3.5731***	1.2624***	-31.6862***
	(0.0237)	(0.1919)	(0.0035)	(0.0971)
DTI-Ratio	-0.1235***	-0.1968***	-0.0925***	1.2169***
	(0.0031)	(0.0130)	(0.0004)	(0.0125)
Weekend Fixed Effect	Yes	Yes	Yes	Yes
Active Time Fixed Effect	Yes	Yes	Yes	Yes
Observations	2,525,391	2,525,391	2,525,391	2,525,391
R-squared	0.2497	0.1276	0.5518	0.1058

This table present the results for model (3.1) with *Invest Profit*, *Invest Return* and *Sharpe Ratio* as the dependent variables. *Invest Profit*, which is defined as the he logarithm of profit of the bid made by the investor. *Invest Return,* which is defined the rate of return in which an investor could receive from the bid. *Sharpe Ratio*, which is defined by the ratio between the profit of an investment and the risk of the investment. *Fake Holiday* dummy is defined by the period one week before- and after-holiday. The rest of independent variables remain the same setting as Table 3.3. In all estimations, loan fixed effect, weekend fixed effect and active-time fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Table 3.10: Extensions: Post Holiday effects

	(1)	(2)	(3)
	Time on Market	**Invest Return**	**Sharpe Ratio**
Post Holiday	0.3026***	-0.0201***	0.0241
	(0.0240)	(0.0035)	(0.0981)
Loan Amount	1.2636***	-0.1088***	0.6213***
	(0.0084)	(0.0012)	(0.0344)
Log (Bidders)	-1.1357***	-0.0410***	-0.0010
	(0.0044)	(0.0006)	(0.0181)
Log (Loans)	-0.0002***	0.0001***	0.0005***
	(0.0000)	(0.0000)	(0.0000)
Risky	2.1365***	1.2622***	-31.6865***
	(0.0237)	(0.0035)	(0.0971)
DTI-Ratio	-0.1230***	-0.0926***	1.2169***
	(0.0031)	(0.0004)	(0.0125)
Weekend Fixed Effect	Yes	Yes	Yes
Active Time Fixed Effect	Yes	Yes	Yes
Observations	2,525,391	2,525,391	2,525,391
R-squared	0.2498	0.5518	0.1058

This table present the results for model (3.1) with *Time on Market*, *Invest Return* and *Sharpe Ratio* as the dependent variables. *Post Holiday* dummy is defined by the three days' period since the first working day post the holiday. The rest of independent variables remain the same setting as Table 3.3. In all estimations, loan fixed effect, weekend fixed effect and active-time fixed effect are included but not reported. Robust standard errors are in parentheses. *, **, and *** indicate significant level at 10%, 5%, and 1%, respectively.

Appendix

Appendix Table TA3.10 presents the definitions of variables used in the estimations based on Renrendai dataset.

Appendix Table TA3.11 presents the definitions of variables used in the estimations based on Bondora dataset.

Table TA3.10: Definitions of variables used in Renrendai estimation.

Variable	**Definition**
Time on Market	The time gap between a loan is posted to the investor bids to the loan (measured by hours).
Modified Time on Market	The time on market controlled by the total hours of entire fundraising progress of the loan listing.
Relative Position	The order of the investor bids controlled by the total number of bids which the loan receives from the entire fundraising progress.
Invest Profit	The logarithm of profit of the bid made by the investor.
Invest Return	The rate of return in which an investor could receive from the bid (measured by percentage points).
Sharpe Ratio	The ratio between the profit of an investment and the risk of the investment (measured by percentage points).
Loan Amount	The logarithm of requested amount of the loan listing.
Log (Bidders)	The logarithm of the number of active investors on the market in a particular date.
Log (Loans)	The logarithm of number of loan applications being listed on the market in the date.
DTI Ratio	Ratio of borrower's debt divided by monthly income
Risky	If = 1, the listing’s credit grade is E or below, i.e. E or F or HR, else 0
Failed Outcome	If = 1, the listing is tagged as failed as it cannot raise enough amount funding, else 0
Borrowing Cost	Percentage rate of interest on the loan offered by the borrowers.
Fulfilled Hour	Bidding time period for a loan requests in hours

Table TA3.11: Definitions of variables used in Bondora estimation.

Variable	**Definition**
No. of Notes	The number of current notes normalized by the number of listed days in the current date for a P2P loan.
Discount	The average notes price (discount rate measured by percentage) asked by the sellers in the current date for a P2P loan.
Share. of Success	The share of notes sold successfully of the same loan during the current date.
Share. Type 1 error	The share of notes listed by type 1 error for the same loan during the current date.
Share. Type 2 error	The share of notes listed by type 2 error for the same loan during the current date.
Share. error	The share of notes listed by type 1 or type 2 error for the same loan during the current date.
Loan Age	The logarithm of one plus the maturity of the loan (measured in months)
Outstanding Principal	The share of outstanding principle in the current week out of the original principle
Log (Loans)	The natural logarithm of one plus the number of current notes posted by the sellers on the secondary market in the current week

Conclusion

This thesis studies several important determinants of investor behaviour that currently receive limited attention from the previous literature in peer-to-peer online banking markets. In the first chapter, we introduce a critical phenomenon of behavioural economics, namely expert imitation, by investigating the online investing dataset of individual investors. This study documents that the P2P investors might learn and imitate the biddings made by influential investors. In particular, we employ unique network centrality technique to help us to understand the influence of each investor. The unique measurement of investor centrality, as well as the investment intensity of investors, provide a valuable opportunity to identify the expert/opinion leader in the online investor community. This study, for the first time, provides the evidence that observational learning happens in P2P environment and general individuals observe and follow market leaders' biddings.

Our expert detection measurements employ sequences of rolling windows over historical biddings. Consequently, we identify some investors as experts according to investor bidding intensity and network centrality measures. All these methods could successfully identify those top investors in the online community. We then introduce these measurements into an empirical model which has been employed to detect the existence of herding. The results show that, the bidding decision given by experts significantly and positively relates to the lending decisions of the remaining investors in the online market. That is, we document that the investors observe and learn from those influential experts and follow the expert behaviour.

Furthermore, we find that the expert imitation exhibits heuristics properties. Our estimations based on investor experience on the market shows that, those new investors who have only a few biddings on the market do not particularly act in line with experts, thus they still show strong tendency to herd. We explain this bear in mind that the new investors have not observed enough biddings to identify experts, therefore, they are more likely to simply act in the crowd. Interestingly, experts do not follow other experts in the community. However, experts still exhibit the tendency to herd the crowd. These findings might suggest that, expert imitation requires observing and learning, whereas herding is ultimately subconsciously inherent in human natures.

In the second chapter, we evaluate the link between official C19 information and investor decision dynamics. This study provides evidence that European P2P investors exhibit negative pricing movements in response to Spanish C19 information. Also, we find a stronger effect of country-level C19 news compared to regional level news. This study further explains the regional inattention by investigating the role of information transmission channel. Indeed, we suggest that the inattention on regional C19 updates might be attributable to the insignificant media coverage and information demanding of C19 regional topics.

We first illustrate how P2P investors learn and acquire the C19 announcements. The findings from our fixed effect model suggest that, sellers ask lower price in response to the ongoing Spain C19 cases. Sellers' willingness on trading is decreased within the increasing C19 case updates. In contrast, buyers are more likely to accept the lower asked price as the success rate of transaction increases. Compared to the nation-wide statistics, regional C19 updates are only moderately associated to investor decisions. That is, investors rely more on Spain-wide C19 news, whereas they are less-attentive to regional information.

We further explore the investor inattention to the regional C19 updates. We posit this inattention might be related to the insignificant transmission channel region-level C19 topics. This study proxies the information transmission channel by utilizing media attention proxies on both nation- and region-level. It is worth to note that, the transmission channel is measured by both demanding and supply of C19 information. Introducing the transmission channel proxies to the baseline model, our estimates conduct that the inattention on regional terms is associated to the insufficient micro media attention and limited information supply. The investors do not have enough motivation to learn the regional updates, likewise, they are not equipped with adequate exposure to the detailed information.

This study is extended by several extensions. First, we exploit whether the mismatch beliefs on asset valuation between sellers and buyers are affected by C19 updates. The findings indicate that, the C19 announcements narrows the dispersed beliefs on the asset valuation between sellers and buyers, buyers are willing to accept the lower prices favoured by sellers. Second, this study examines the role of lockdown stringency on investor decisions. After including the lockdown stringency proxies, the results suggest that the restricted lockdowns could enhance the downward asset price movements and higher valuation agreements.

In the third chapter, we evaluate the connect between the public holidays and investor behaviour. Differs from the previous literature focuses on the investor attention before- and after- the non-trading holidays, this study extends the understanding of holiday effect, a well-documented behavioural issue in the financial market by initiating the investigation on holiday trading behaviour. We employ data extracted from two leading P2P lending platforms from continental Europe and mainland China. The estimations on two different platforms based in two P2P marketplaces with disparate cultural habitudes and holiday schedules echoes with each other, suggesting the celebration of holiday might be responsible to the investor holiday distraction.

This study documents that investors are more inattentive to the holiday trading in both primary and secondary market. Our baseline estimates suggest that, both European and Chinese investors tend to spend longer time to make financing decision during public holidays. That is, investor decision time during public holidays is significantly higher than normal calendar dates. Furthermore, the investors are more likely to make inferior decisions compared to the regular trading days. Individual P2P investors, both lenders in primary loan market and sellers/buyers in secondary market, are acting worse in holidays compared to their usual decision quality.

We extend this study by implementing a further test based on the experience of investors in primary market. Examining the holiday distraction on investors who have different experience on the market, this study documents that the holiday distraction could play as heuristics learning. Although the decision-making progresses of both rookies and veterans are delayed during holidays, the experienced investors are most likely to be affected by the holiday distraction as they make more inferior decisions. This extension indicates that the celebration of public holiday is unavoidable for most market participants, whereas the experienced investors shows more inattention to the holiday financing issues.

Future Works

This thesis investigates several valuable determinants of investor behaviour that currently receive limited attention from the previous literature in peer-to-peer online banking markets. However, there are still several valuable research opportunities.

In the first chapter, we investigate the phenomenon of expert imitation, general individuals tend to learn and follow the investment strategies from influential investors. This chapter also examines the existence of herding behaviour among investor community. Similar to the herding behaviour, the peer effect is also widely investigated in the empirical finance literature. For instance, Yan and Zhu (2020) apply the momentum of peers to proxy the peer effect. The future studies would benefit from the discussion on the difference between peer effect and herding behaviour in P2P lending environment.

In the second chapter, we examine whether the updates of Spanish COVID-19 information would affect the asset pricing dynamics in a P2P secondary market. The Diff-in-Diff strategy has been applied by the recent studies focusing on the COVID effect on financial market. However, as this chapter focuses on the development of C19 outbreak in Spain and its regions, we collected the Google trend index for “Spain + Covid (and coronavirus)”, as well as “Region Name + Covid (and coronavirus)”. The same strategy is applied in the online newspaper articles. Therefore, the media coverage and online attention proxies used in this chapter do not allow us to trace back to the pre-pandemic phase. We believe the combination between Diff-in-diff strategy and the role of COVID-19 media attention would provide an important insight for the future research.

In the third chapter, we examine the abnormal holiday trading behaviour in P2P lending environment. Also, this chapter finds that the holiday effect exhibits heuristic features as the experience of investors could affect the trading pace in the holidays. In the chapter 1, we identify the active influential investors as experts. Therefore, it would be valuable opportunity to link expert activity and investors’ holiday trading on the market.

In the first chapter, we use rolling window strategy to identify the experts, so the expert list would be updated in month by month. Therefore, it might be difficult to link the expert identity and investor experience in the current stage. In the future works, we will explore whether the expert identification strategy could be modified to fit in more general investigations.

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