P2P Lending Survey: Platforms, Recent Advances and Prospects

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P2P lending is an emerging Internet-based application where individuals can directly borrow money from each other. The past decade has witnessed the rapid development and prevalence of online P2P lending platforms, examples of which include Prosper, LendingClub, and Kiva. Meanwhile, extensive research has been done that mainly focuses on the studies of platform mechanisms and transaction data. In this article, we provide a comprehensive survey on the research about P2P lending, which, to the best of our knowledge, is the first focused effort in this field. Specifically, we first provide a systematic taxonomy for P2P lending by summarizing different types of mainstream platforms and comparing their working mechanisms in detail. Then, we review and organize the recent advances on P2P lending from various perspectives (e.g., economics and sociology perspective, and data-driven perspective). Finally, we propose our opinions on the prospects of P2P lending and suggest some future research directions in this field. Meanwhile, throughout this paper, some analysis on real-world data collected from Prosper and Kiva are also conducted.

CCS Concepts: • **Information systems** → Information systems applications; • **Applied computing** → *Social and behavioral sciences*; Economics; • **World Wide Web** → Web applications;

Additional Key Words and Phrases: P2P lending, micro-finance, online loans, platforms, prospects

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1. INTRODUCTION

Peer-to-peer lending, often abbreviated P2P lending, is the practice of lending money to individuals or businesses through online services that match lenders directly with borrowers.[1] Since the P2P lending companies offering these services operate entirely

[1]https://en.wikipedia.org/wiki/Peer-to-peer_lending.

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online, they can run with lower overhead and provide the service more cheaply than traditional financial institutions. Thus, through online trading, P2P lending makes micro-finances or small loans possible without going through any traditional financial intermediaries [Wang et al. 2009; Berger and Gleisner 2009; Bachmann et al. 2011]. In recent years, P2P lending has become a fast-growing market that attracts many users (borrowers and lenders) and generates massive transaction data. For instance, the world's largest P2P lending platform (i.e., LendingClub[2]) announced its total loan issuance amount had reached more than $ 24.6 billion by the end of 2016.

Since the first P2P lending platform (i.e., Zopa[3]) was established in 2005, more and more different types of P2P lending platforms have emerged (e.g., Prosper[4], LendingClub, Kiva[5] and Renrendai[6]). These platforms work under different mechanisms, including trading rules and risk managements. In this article, we provide a systematic taxonomy for P2P lending by summarizing different types of mainstream platforms and comparing their working mechanisms in detail, which we believe has not been done yet in the literature.

Given the rapid development of P2P lending and the availability of its transaction data, many research works have been done in the past. Most of the existing works look into P2P lending problems mainly from the economics and sociology perspective (e.g., platform mechanism [Hulme and Wright 2006], social community analysis [Herrero-Lopez 2009; Freedman and Jin 2008; Greiner and Wang 2009]), and data-driven perspective (e.g., risk evaluation [Klafft 2008a; Luo et al. 2011; Byanjankar et al. 2015; Guo et al. 2016], fundraising analysis [Ryan et al. 2007; Herzenstein et al. 2008], and lending or bidding behavior [Shen et al. 2010; Ceyhan et al. 2011]). In this article, we make our efforts to provide a comprehensive review about these recent works in P2P lending. Especially when reviewing the data-driven works, we will demonstrate some analysis results with the real-world data. In fact, with the purpose of attracting researchers' attention and promoting the advance of P2P lending, more and more platforms such as Prosper, LendingClub,[7] and Kiva[8] have released some of their data for academical research. We have collected a large amount of data from Prosper and Kiva. After preprocessing these collected real-world data, we publish them in http://home.ustc.edu.cn/%7Ezhhk/DataSets.html.

Finally, we present our opinions on the prospects of P2P lending and suggest several future research directions in this field, such as pricing, mechanism improvement, risk management, privacy, and personalization. To the best of our knowledge, this article is the first comprehensive survey on P2P lending that includes not only a summary of existing P2P lending platforms and a review of recent research works but also the prospects and future research directions.

The rest of this article is organized as follows. In Section 2, we introduce the mainstream platforms and summarize their working mechanisms, respectively. In Section 3, we systematically review and organize the recent research works in P2P lending. In Section 4, we introduce our opinions on the prospects of P2P lending and suggest some future research directions in this field. Finally, we conclude our work in Section 5.

[2]https://www.lendingclub.com/.
[3]http://www.zopa.com/.
[4]https://www.prosper.com/.
[5]http://www.kiva.org/.
[6]http://www.renrendai.com/.
[7]https://www.lendingclub.com/info/download-data.action.
[8]http://build.kiva.org/docs/data.

2. PLATFORMS

In 2005, the first P2P lending platform in the world (i.e., Zopa) was founded in the United Kingdom. Since then, more and more P2P lending platforms have been created [Frerichs and Schuhmann 2008; Bachmann et al. 2011]. At present, the world's largest lending platform is LendingClub, which has totally accumulated about $24.6 billion transactions. In the early days of P2P lending, it was regarded as a high-risk high-return investment way by investors. With the emphasis on the risk management of lending platforms, many large platforms intend to guarantee investors' profits. In the meantime, many governments provide more and better supporting policies for the development of P2P lending. According to incomplete statistics by 2015, online marketplace loan origination in United States has doubled every year since 2010. Moreover, the trend is playing out globally, notably in Australia, China, and the United Kingdom. Specifically, P2P lending could command $150 billion to $490 billion globally by 2020.[9]

The recent development of P2P lending becomes more diverse and functionally special. Besides the general lending platforms (e.g., Prosper, LendingClub), a lot of platforms in some specific domains are emerging, such as AgFunder for agriculture[10] and Kiva for charity. Most of these lending platforms charge very little (e.g., Prosper) and even charge nothing (e.g., Kiva) from loan transactions. Due to the simple and efficient working mechanism, P2P lending attracts more and more users. Consequently, P2P lending platforms have greatly helped individual borrowers and small enterprises solve their financing problems, and also provided lenders or investors with an optional wealth-management way.

Although extensive platforms have been established in the world, there has not been yet an unified classification and summary for them. In the rest of this section, we provide a detailed summary of P2P lending platforms. Specifically, we will carry out from mainstream platforms and their working mechanisms, respectively.

2.1. Mainstream Platforms

In this subsection, we first provide a taxonomy for P2P lending along different dimensions, and then introduce several representative P2P lending platforms in the world.

2.1.1. Taxonomy. Figure 1 shows a taxonomy of P2P lending platforms based on three classification dimensions. In the following, we describe each of these dimensions.

Application Domain. Based on the application domains, P2P lending platforms can be classified into two categories (i.e., *general platforms* and *professional platforms*). General platforms are designed for any individuals and small enterprises no matter of their borrowing purposes or motives. Most early P2P lending platforms are general ones, such as Prosper and LendingClub. In recent years, many professional platforms designed for some specific application domains are emerging. For example, AgFunder is an online investment marketplace enabling accredited investors to invest in agriculture and agriculture technology companies, and Kiva is a non-profit charitable organization with a mission to connect people through lending to alleviate poverty mostly in developing countries.

Trading Rule. Based on their adopted trading rules, P2P lending platforms can be classified into two categories, that is, *auction-based platforms* (e.g., Prosper) and *non-auction-based (i.e.,* fundraising-based*) platforms* (e.g., LendingClub, Kiva). The details of trading rule are complicated and will be specifically introduced in Section 2.2.4.

[9]http://www.morganstanley.com/ideas/p2p-marketplace-lending.
[10]https://agfunder.com/.

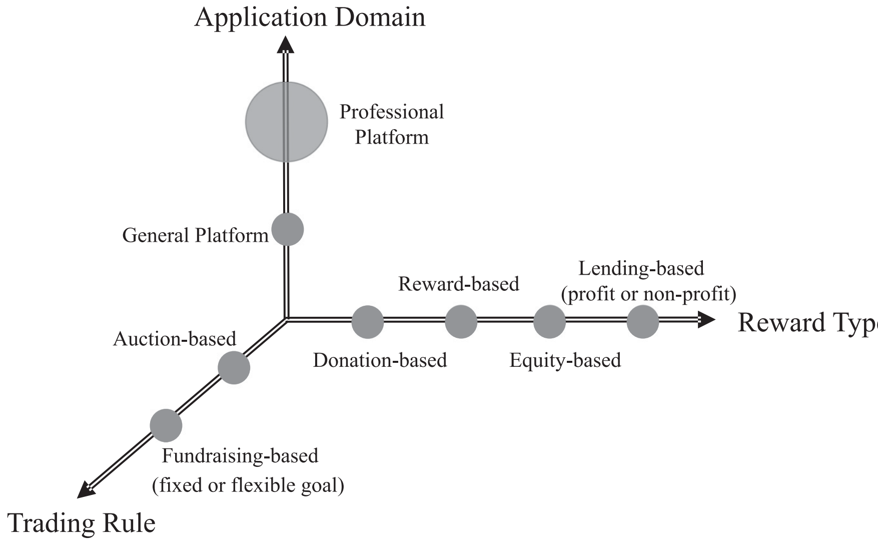


Fig. 1. Taxonomy of P2P lending.

Reward Type. Different platforms have different strategical goals and driving factors. Some platforms are with a mission of helping the people in poverty, some others want to encourage the creative ideas, while some others are providing a way for investment or shopping. Different goals determine their adopted reward types. Based on the different types of reward for lenders, P2P lending platforms can be mainly classified into four categories, that is, *donation-based*, *reward-based*, *equity-based,* and *lending-based platforms* [Haas et al. 2014; Deeb et al. 2015]. In donation-based platforms, donors donate money to fund a venture in order to help launch a product or service, or help others with dreams or in trouble. For example, GoFundMe[11] is a typical donation-based platform. In these platforms, individuals donate some money to a fundraising campaign with receiving no reward or just a "thank-you" note. Reward-based platforms follow a model in which a funder's primary objective for funding is to gain a non-financial reward [Haas et al. 2014; Deeb et al. 2015], such as Sellaband and Kickstarter. Reward-based platform is similar to donation-based platform in that funders give money to ventures without an expected financial return, but funders are guaranteed to receive a reward. In equity-based platforms, funders can receive compensation in the form of the entrepreneur's equity-based or profit-share arrangements. Furthermore, the return of a funder on investment correlates with how well the company performs. For example, Crowdfunder[12] is a leading equity-based platform. The reward-based and equity-based platforms are also considered as the typical forms of *crowdfunding* in the narrow sense.

Lending-based platforms follow the typical lending mechanism, in which funders/lenders receive fixed periodic income and expect repayment of the original principal investment. Examples of such platforms include Prosper and LendingClub. Kiva is a special case of lending-based platform, in which borrowers only need to repay the principal to each lender without any interest. In this article, we mainly study the lending-based platforms that are treated as the typical P2P lending form in the narrow sense, such as Prosper (profit platform) and Kiva (non-profit platform).

[11]https://www.gofundme.com/.
[12]https://www.crowdfunder.com/.

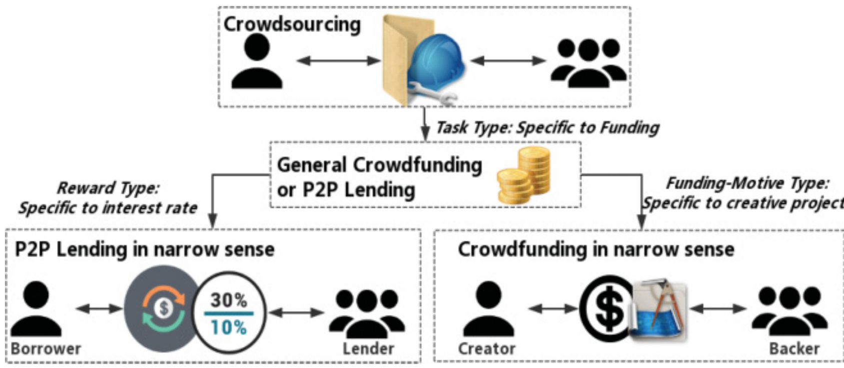


Fig. 2. Relationship of P2P lending, crowdfunding, and crowdsourcing.

P2P lending Versus Crowdfunding. Many times, P2P lending is confusing with crowdfunding [Hemer 2011; Belleflamme et al. 2014; Deeb et al. 2015; Beaulieu et al. 2015]. In general, crowdfunding is the process of raising small amounts of money for a project or venture by a large number of people typically through an online platform. From the view of *borrowing-money or funding motives*, we can treat crowdfunding as a special case of P2P lending. Most funding campaigns in crowdfunding are creative projects, for example, software development, invention development, or from startup companies. In P2P lending, the borrowing purposes are much more diverse (e.g., debt consolidation, home improvement). Of course creative projects are also included. However, on the other hand, as we described in the *reward-based classification dimension*, P2P lending sometimes refers to the narrow definition of lending-based crowdfunding [Haas et al. 2014; Deeb et al. 2015]. Thus, from this point of view, we can consider reward-based crowdfunding, equity-based crowdfunding, donation-based crowdfunding and lending-based crowdfunding (P2P lending) all belong to the category of general crowdfunding. More broadly speaking, both P2P lending and crowdfunding are specific practices of crowdsourcing[13] in business or finance. Their relationships are shown in Figure 2. In this artilce, we mainly focus on one type of platform: lending-based platforms or typical P2P lending in the narrow sense, such as Prosper and Kiva.

2.1.2. Representative Platforms. After providing the taxonomy for P2P lending, we introduce several representative platforms in the world.

Prosper. Prosper is the first P2P lending marketplace in America founded in 2005, with more than 2 million members and over $5 billion in funded loans until November 2015. Prosper allows individuals to invest in each other in a way that is financially and socially rewarding. In Prosper, borrowers list loan requests between $2,000 and $35,000 and individual lenders invest as little as $25 in each loan listing they selected. Prosper handles the servicing of the loan on behalf of the matched borrowers and lenders.[14] Besides, Prosper also holds a credit profile for every borrower. A credit profile is a set of extended credit information for a member including credit grade/rating, which is estimated by Prosper from the highest level “AA” to the lowest level “HR” (High Risk). Whenever a loan is listed, the borrower’s credit grade is shown with the loan. Prosper also allows customers (both borrowers and lenders) to found groups. Borrowers in a

[13]Crowdsourcing is the process of obtaining needed services, ideas, content (or even money) by soliciting contributions from the crowd, and especially from an online community. For more details, please refer to Brabham [2013], Garcia-Molina et al. [2016], or Wikipedia (https://en.wikipedia.org/wiki/Crowdsourcing).
[14]https://www.prosper.com/about.

Table I. A Summary of Representative Platforms

Platform	Prosper	LendingClub	Zopa	Renrendai	Kiva
Country	USA	USA	UK	China	USA
Area	USA	USA	UK	China	World-wide
Founded	2005	2006	2005	2010	2005
Data Release	Nov 2015	Dec 2016	Nov 2015	Mar 2015	Nov 2015
Loans	\$5 billion	\$24.6 billion	£1.18 billion	CNY 720 million	\$781 million
Members	2,000,000	Unknown	213,000	1,500,000	1,351,777
Charge fees	Yes	Yes	Yes	Yes	No
Category	General Auction(early) Lending-based	General Fundraising Lending-based	General Auction Lending-based	General Fundraising Lending-based	Professional Fundraising Lending-based

group benefit from the group's credit level, and their behaviors also influence the credit level of the entire group.

LendingClub. LendingClub is now the world's largest online P2P lending marketplace. The platform not only provides personal loans but also facilitates business loans and financing for elective medical procedures.[15] LendingClub adopts a similar working and trading mechanism with Prosper's.

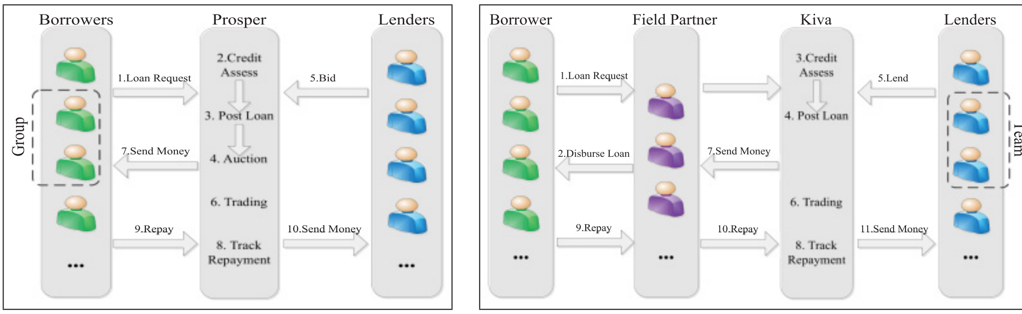
Zopa. Zopa is the world's first online P2P lending platform in the United Kingdom, which has lent more than £1.18 billion up to November 2015. Founded in 2005, this platform now keeps over 150,000 borrowers and more than 63,000 lenders including 53,000 active. Zopa has some of the lowest default rates in the industry because Zopa is very selective about borrowers. Across all loan products, a borrower's money is automatically spread across multiple sensible borrowers to diversify risk. Zopa in conjunction with a not-for-profit company called P2PS Limited will administrate the default loans.[16]

Renrendai. Renrendai is one of the first peer-to-peer lending platforms founded in May 2010, in China. Renrendai has more than 1,500,000 members and has lent over CNY 720 million in loans until March 2015.[17] Renrendai charges fees from borrowers. One part of the fees is collected to fill the loss provision account, another part is the income of the platform. Renrendai charges the loss provision fee in different rates according to the credit levels of borrowers.

Kiva. Kiva is a non-profit organization with a mission to connect people through lending to alleviate poverty. The Kiva organization is the first to pioneer zero-interest entrepreneurial lending [Hartley 2010]. Until November 2015, Kiva has 1,351,777 lenders and \$781 million in loans. Leveraging the internet and a worldwide network of microfinance institutions, Kiva lets individuals lend as little as \$25 to help create opportunity around the world. Kiva is a non-profit platform, which means Kiva does not take a cut from loans, and borrowers only need to repay the principal to lenders without any interest.[18] Different from the aforementioned platforms in which lending is mainly for interest rate or profit, in Kiva, lenders' lending behaviors are more determined by their interests or the stories of borrowers.

These platforms all belong to the lending-based ones in terms of reward type (i.e., typical P2P lending in the narrow sense). We provide a summary of the aforementioned platforms in Table I. Among these platforms, Prosper and Kiva are the two most representative ones that cover most different working mechanisms. Thus, in the following, we take them as examples to illustrate the working mechanisms of P2P lending.

[15] https://www.lendingclub.com/public/about-us.action.
[16] https://www.zopa.com/lending/risk-management.
[17] http://www.renrendai.com/about/about.action?flag=intro.
[18] http://www.kiva.org/about.



(a) Prosper (b) Kiva

Fig. 3. The working mechanism overviews of Prosper and Kiva.

2.2. Working Mechanisms

As we described earlier, many platforms work under different working mechanisms. Their working mechanisms can be grouped into two types. Prosper and Kiva are the representative examples of each type, respectively. Figure 3 shows their working mechanism overviews. In this subsection, we will look into these mechanisms. Specifically, we first introduce the main members in Prosper and Kiva, and then present their working flows. Besides, in this subsection, we also introduce the platforms' roles on managing risk and trading rules they use.

2.2.1. Members. In order to easily understand the working mechanisms, in this part, we first introduce the important members in these P2P lending platforms.

Borrower. No matter in which platforms, a borrower (denoted as ub_i) is someone who wants to borrow money through P2P lending markets. In Prosper, they must be a citizen of the United States. But Kiva, whose aim is to help more poor people improve their lives in the world, has borrowers who are mainly concentrated in developing countries. Due to different working mechanisms, the responsibility of the borrower in Prosper is different from that in Kiva. In Prosper, a borrower first needs to register her personal information for the most basic credit inquiry, provide a proposal to tell what she needs the money for, and set an accept interest rate as bottom line, and then post a customized loan listing (denoted as v_j). With the auction or soliciting bids from lenders in a fixed period, if the loan listing is fully funded, the borrower needs to repay the principal and interest in installments for her loan.

In Kiva, a borrower does not trade on the platform directly but through *field partner*, which will be introduced later. Borrowers in Kiva provide their information and borrowing-money purposes to field partners, and they do not need to set interest rates because of the non-profit nature of Kiva. Field partners rather than borrowers will post the loan listing on Kiva. In the end, borrowers need to repay the principal for their loans also via the field partners.

Lender. Lenders are also known as investors in Prosper (and donators in Kiva). In Prosper, a lender (denoted as ul_i) sets an investment criteria, finds suitable loan listings, and then invests the selected loans. Lenders in Prosper have different focuses and practices from those in Kiva. While most lenders in Prosper focus on the profits they could earn, most lenders in Kiva pay most of their attention to the stories of loans and essentially want to help borrowers. However, lenders in both Prosper and Kiva have to assume the risk of loan default.

Field Partner. The connection mechanism to borrowers in Kiva is not the same as that in Prosper (as shown in Figure 3). Kiva is not directly connected to borrowers but through some local organizations such as microfinance institutions (MFIs), social enterprises, schools, and non-governmental organizations (NGOs). These institutions are called *field partners* (denoted as uf_i) in Kiva, which are ground links to borrowers. They perform their jobs mainly in two aspects.[19] First, they need to review loan applications and post loan requests and stories on Kiva. Second, they are responsible for the disbursement and repayment collection of loans. If a borrower's core business is microfinance, then she is vetted by the field partner in Kiva. A field partner reviews the loan mainly based on her experience with the borrower, including the borrower's future earnings and the borrower's capability to repay. Once a loan is approved, the field partner posts the borrower's profile information about her picture and a description of the loan on Kiva. When lenders lend money to borrowers, Kiva delivers the fund to the local field partner, so field partners have the second job. Depending on their conditions, field partners can choose to disburse the funds to borrowers or use the funds to backfill a loan (that has already been disbursed to the borrower by her in order to promote the use of capital and reduce the waiting time of the borrower). Besides, borrowers are required to pay the full amount due to local field partner. Typically, the field partner will travel to borrower's location, such as rural village, and collect a repayment regularly, (e.g., monthly).

Kiva assesses each field partner with a risk rating based on her financial audit, organizational experience, and existing loan portfolio size and risk. Risk ratings are qualitative one-to-five star ratings. Field partners with a one-star risk rating can post up to \$10K in loan requests per month, while a five-star rated field partner can post up to \$100K in entrepreneur requests. In this way, Kiva additionally helps regional field partners establish credit histories by allowing even historically poor performers to request loans to build a positive portfolio [Hartley 2010]. After introducing the important members in P2P lending, let us introduce two types of communities (i.e., *Groups* in Prosper and *Teams* in Kiva).

Group. In Prosper, both borrowers and lenders who share a common interest or affiliation can form groups (denoted as $G_i, G_i = \{u_1, \ldots, u_{|G_i|}\}$, where u_i is either a borrower or a lender). As a type of smaller community within this marketplace, a group helps translate into low rates for borrowers and low risk of defaults to lenders. Of course, each group needs to run under the leadership of someone, so there is a *group leader*. The group leader manages her group by bringing borrowers to the platform, maintaining the group's presence on the site, and collecting/sharing group rewards. Through understanding the duty of group, we know that the group leader acts like a new "financial intermediary." For instance, Ryan et al. [2007] found that having a group leader endorsement strongly increases both the percentage funded (+33.8%) and the number of bids (+18.85) on loan listing.

Team. In Kiva, a team (denoted as T_i) is made up of many lenders who have the same hobby, school affiliation, or location (i.e., $T_i = \{ul_1, \ldots, ul_{|T_i|}\}$). The Kiva team only contains lenders, which is different from the group in Prosper that may contain both borrowers and lenders. In Kiva, lenders can act individually or join teams to attribute their preferred loans to a collective campaign or to compare their joint impacts with other like-interest, regional, or demographic groups [Hartley 2010]. A lender may be affiliated with different teams, and a team could contain lenders who are interested in funding one particular type of loans. The most advantage of team is that lenders could collaborate in locating and lending loans. Since lending teams are self-organized by lenders, what they need to do is like the behaviors of lenders (e.g., selecting or contributing to loans) in Kiva. Besides, teams have the authority to vote on whether to approve an organization becoming a field partner of Kiva.

[19]https://www.kiva.org/about/risk/field-partner-role.

2.2.2. Working Flows. After introducing the main members in P2P lending platforms, we then show the typical working processes for loan transactions in Prosper and Kiva. Figure 3(a) shows the working process of Prosper. We explain each step in a nutshell as follows. (1) A borrower ub_i requests a loan v_j in Prosper. (2) Prosper audits the credit level of this borrower. (3) Once the borrower passes the review, Prosper posts the loan listing with detailed information. (4) Then an auction or fundraising begins. (5) Lenders (denoted as UL, $UL = \{ul_1, \ldots, ul_{UL}\}$) start to bid the loan listing with their ideal interest rates. (6)&(7) At the end of auction/fundraising, if this loan can be fully funded, Prosper delivers lenders' money to borrowers. (8) Prosper monitors the process of each borrower's repayments. (9) Borrowers regularly repay money to Prosper. (10) At last, Prosper sends a borrower's repayments deposited directly to lenders' accounts.

Similarly, we explain each step in Figure 3(b) to understand the working process of Kiva. (1) A borrower ub_i requests a loan v_j to a field partner uf_i with her borrowing motivation. (2) Then the field partner decides to disburse this loan or not with the evaluation for this borrower. (3) If a field partner disbursed this loan, she delivered this loan request and story to Kiva, which reviews this loan in many aspects include credit assess. (4) If a loan pass the review, then field partner disburses the loan on Kiva. (5) Lenders (UL) browse different loans and lend their money to loans. (6)&(7) Kiva receives the funds and sends money to field partner via wire transfer. (8) Kiva needs to track the repayment for lenders. (9) Borrowers repay a certain amount of money to local field partner regularly. (10) The field partner collects the repayment to Kiva. (11) Finally, Kiva returns money to lenders and lenders can choose to donate it to Kiva or lend it to other borrowers.

2.2.3. Risk Management. In this part, we introduce the platforms' roles on risk management. As a medium of information carrier, P2P lending is more like a *broker* who provides alternative investment projects for the lender and finds investors for the borrowers. Compared with the traditional financial loans, P2P platforms cut off the role of financial intermediaries. Thus, in addition to providing a media for information exchange and trading, these platforms also has the responsibility to manage risk, that is, reducing the default probabilities of borrowers. We introduce the risk managements in Prosper and Kiva, respectively.

Risk management in Prosper. For managing risk, Prosper designs a credit system for borrowers, that is, assessing each borrower with a credit rating (from the highest level "AA" to the lowest level "HR"). Beyond that, Prosper is more concerned about protecting each user's privacy whether you are a borrower or a lender. When borrowers tell potential investors the reasons why they are looking for a loan, their actual identities are never revealed. For investors, Prosper offers an ID Theft Guarantee to avoid fraudulent borrowers. In a nutshell, Prosper is not merely a platform for exchanging information but also a fraud defender.

Risk management in Kiva. The responsibilities of Kiva and Prosper are similar, but the difference is that Kiva designs a credit system for field partners instead of borrowers. In order to protect the profits of lenders and reduce the risk of the platform, Kiva has deployed multiple credit measures mainly aiming at the field partners. The first one is developing a system of credit tiers to strictly distinguish different risk levels of field partners. The second one is to conduct due diligence on all field partners before allowing them to begin posting loans on the platform. In this case, Kiva reviews applications from potential field partners. If necessary, the field partners will visit the organization for on-site due diligence. Then the field partner prepares a due diligence report includes some components such as borrower cost analysis, financial analysis, proposed risk rating, and proposed social performance badges. Finally, a field partner submits the due diligence report to members of lending team for approval. The third one is ongoing monitoring of existing field partners. According to different partner's credit tier, Kiva has various activities. For example, a field partner in the lowest credit tier does not have a risk rating, whereas Kiva needs to update of the risk model and associate risk rating for a high-level credit tier partner.

2.2.4. Trading Rules. In Section 2.2.2, we describe the basic working flows in Prosper and Kiva without their trading details. In this part, we introduce two widely adopted trading rules in P2P lending platforms: one is the *auction-based trading rule* (e.g., adopted by Prosper and Zopa) and the other is the general *fundraising trading rule* (e.g., adopted by LendingClub, Kiva, etc.).

Auction. In Prosper, or other typical profit platforms, lenders or investors always pursue maximum profits. The interest rate is the most important factor affecting the lending transaction. In these platforms, auction is needed. Trading in Prosper follows the *Dutch Auction Rule* [Kumar and Feldman 1998]. Chen et al. [2014] analyze the Prosper auction as a game of complete information and fully characterize its Nash equilibria. The details of auction rule in Prospers are as follows.

Specifically, for borrowing money, a borrower will first create a loan *listing* (requirement specification) to solicit bids from lenders by describing herself, the reason of borrowing money (e.g., for a wedding), the required amount (e.g., $1,000), and the maximum interest rate (e.g., 10%) she can accept. Besides, the listing also contains the borrower's credit information and the listing's soliciting duration. Then, if a lender wishes to invest on this listing within its soliciting duration (e.g., 1 week), a bid is created by her describing how much money she wants to invest (e.g., $50) and the minimum rate (e.g., 9.5%). If a listing receives more bid amount in its soliciting duration than the required amount, competition among bids will occur, that is, some bids with higher rates will be outbid and fail and the bids with lower rates will succeed. Please note that, for a specific loan, the final treading rate is the same for all winning lenders, which is the maximum rate in all successful bids. The auction follows the "all-or-nothing" principle, that is, if the listing can not receive enough money in time (fully funded), it would be expired and all the previous bids would be also canceled. In Prosper's auction, the credit and preset rate are two of the most important aspects for lenders to assess a loan listing [Ryan et al. 2007; Klafft 2008b; Iyer et al. 2009; Bachmann et al. 2011], which will be detailed in next section. With the bid competition and "all-or-nothing" principle, the winning-bid probability and fully funded probability of each loan are another two important factors considered by lenders when selecting loans. Besides, Prosper instructs lenders to diversify their money on multiple loan listings to reduce risk [Zhao et al. 2014]. Also, in Prosper, most rational lenders have the *portfolio* [Markowitz 1952] perspective in their minds. Thus, in Prosper, usually, a successful loan listing would receive money from more than hundreds of lenders.

As described earlier, the auction rule is complicated especially for the new lenders. Thus, to improve the experience and trading efficiency for customers, most platforms (e.g., Prosper) ended their auction process for trading and take a new fundraising trading.[20] Actually, fundraising (with fixed goals or flexible goals) is another widely used trading rule in both P2P lending and crowdfunding.

Fundraising with a Fixed Goal. Now, most typical P2P lending markets adopt a simple trading rather than competitive auction. Each loan is with a fixed rate and fundraising duration. Fundraising with fixed goals also follows the "all-or-nothing" principle as in the auction. That is, loans still need to receive enough money (reaching the fixed goals) in their durations. Once the receiving money reaching the goal of a loan, the transactions take effect and the loan begins the repayment. The transactions

[20]http://www.lendacademy.com/prosper-com-ending-their-auction-process-dec-19th/.

on the loans that cannot receive enough money will be expired. Similarly, Kiva also adopts this type of trading rule.

Fundraising with a Flexible Goal. Some platforms adopt flexible goals for loans. That is to say, for this kind of loans, there is no need to raise enough money as the raising goals. The transactions are always effective no matter whether the raising will reach the goals or not. On the other hand, the loans can choose to continue to raise money beyond the durations and goals. This kind of trading rule is usually adopted by crowdfunding platforms (e.g., Indiegogo).[21]

3. RECENT ADVANCES

Previous works provide some overview about P2P lending [Wang et al. 2009; Berger and Gleisner 2009; Bachmann et al. 2011; Ruiqiong and Junwen 2014] and introduce the general crowdfunding scenario [Hemer 2011; Belleflamme et al. 2014; Beaulieu et al. 2015]. However, most of these reviews only summarize existing works from one or partial angle and has not provided a comprehensive survey for the studies about P2P lending, particularly recent ones. In the following, we will make our efforts to systematically review and organize the recent research works on P2P lending.

In recent years, P2P lending has attracted many researchers from different backgrounds, such as sociologists and data scientists. Since these researchers from different backgrounds usually study different P2P lending problems from a variety of perspectives, it is difficult to summarize or organize these works from technical views. Thus, we organize these works according to their studied problems and perspectives. Specifically, we group the literature into two categories, that is, works from the *economics and sociology perspective* and works from the *data-driven perspective*. In the first category, researchers mainly study some qualitative problems such as platform mechanism, management, and the society in P2P lending. In the second category, researchers mainly focus on analyzing massive transaction data for some non-trivial goals such as risk assessment, fundraising, and lending behavior analysis. Table II exhibits some representative research in different categories. In the following, we will detail these relevant research.

3.1. Economics and Sociology Perspective

The research works from economics and sociology perspective can be further organized into two categories, that is, *research on platform mechanism* and *research on social community*. The first category of works mainly study the platform mechanism and management in P2P lending. And the second category of works mainly study the society or relationship of users in P2P lending. In this research, some econometric techniques, such as hypothesis testing, are often adopted.

3.1.1. Platform Mechanism. Designing an efficient and securate mechanism is important for better services in P2P lending. Some P2P lending models and platform mechanisms such as Galloway [2009], Wang et al. [2009], and Wei and Lin [2016] have been proposed in the past. These works often refer to some economic considerations, such as *adverse selection* and *information asymmetry*. Adverse selection occurs when borrowers and lenders have access to different information (asymmetric information). Traders with better private information about the quality of a product will selectively participate in trades that benefit them the most (at the expense of the other trader). Along this line, Weiss et al. [2010] presents a novel empirical evidence on the success of efforts by limit adverse selection. Their results show that the screening of potential borrowers is a major instrument in mitigating adverse selection in P2P lending and preventing the

[21] https://www.indiegogo.com/.

Table II. Representative Research.

Research Perspectives		Representative Research	Data	Techniques
Economics and Sociology	Platform Mechanism	[Wang et al. 2009]	Prosper	Comparison Analysis
		[Yum et al. 2012]	Prosper	Hypothesis Testing
		[McKinnon et al. 2013]	Kiva	Case Study
	Social Community	[Lin et al. 2009]	Prosper	Probit, Heckman, Survival
		[Herrero-Lopez 2009]	Prosper	Gaussian Mixture
		[Böhme and Pötzsch 2010]	Smava	Hypothesis Testing
		[Choo et al. 2014a]	Kiva	Maximum Entropy
		[Lu et al. 2014]	Kickstarter	Linear Regression
	Other Research	[Burtch et al. 2013]	Kiva	Hypothesis Testing
		[Ashta and Assadi 2009]	Zopa, etc.	Case Study
Data-driven	Risk Assessment	[Iyer et al. 2009]	Prosper	Regression
		[Emekter et al. 2015]	LendingClub	Survival Analysis
	Fundraising Analysis	[Herzenstein et al. 2008]	Prosper	Logistic Regression
		[Ly and Mason 2012]	Kiva	Linear Regression
		[Mollick 2014]	Kickstarter	Survival Analysis
	Bidding/Lending Behavior	[Herzenstein et al. 2011]	Prosper	Hypothesis Testing
		[Kuppuswamy and Bayus 2014]	Kickstarter	Regression
	Other Research	[Liu et al. 2012]	Kiva	Classification, Regression
		[Zhao et al. 2014]	Prosper	Optimization, Recommendation
		[Zhao et al. 2016b]	Prosper	Optimization, Recommendation

online market to collapse. Freedman and Jin [2011] shows that learning by doing plays an important role in alleviating the information asymmetry between market players, that is, early lenders do not fully understand the market risk but lender learning is effective in reducing the risk over time. Yum et al. [2012] studies the information asymmetry problem by hypothesis testing and finds lenders seek the wisdom of crowds when information on creditworthiness is extremely limited but switch to their own judgment when more signals are transmitted through the market.

In addition to the research on adverse selection, there are also some other research problems about platform mechanism. For example, Wang et al. [2009] discuss different P2P lending marketplace models, how information systems support the creation and management of these new marketplaces, and how they support the individuals involved. Chen et al. [2013] describe a fuzzy set approach to measure the level of entrepreneurship orientation of online P2P lending platforms. McKinnon et al. [2013] analyze the Internet-based discourses through which lenders imagine the intercultural, financial exchange that happens through Kiva's microlending program.

3.1.2. Social Community. As illustrated in Section 2.2.1, social community is an important component in P2P lending services. The social community may affect the members' behaviors and even affect the assessment on borrowers or loans. Thus, social community and borrowers' soft information (e.g., friendship) have been particularly studied in the literature. Especially, in the profit P2P lending platforms (e.g., Prosper), group is the social community which is important for both borrowers and lenders. According to the specific research problems, we can organize the research on social community (in profit platforms) into three categories, that is, the effects of social community on *information asymmetry*, *loan risk and interest rate*, and *loan fundraising*.

Effects on information asymmetry. Berger and Gleisner [2009] finds group leaders in Prosper act as financial intermediaries and significantly improve borrowers' credit conditions by reducing information asymmetries, predominantly for borrowers with less attractive risk characteristics. Lin [2009] studies whether and how network metrics affect the outcome of financial transaction in P2P lending market and finds that relational aspects of the online social network help mitigate information asymmetry in the lending process. Further, Lin et al. [2009, 2013] test whether social networks help mitigate information asymmetry and lead to better lending outcomes. They find stronger and more verifiable relational network measures are associated with a higher likelihood of a loan being funded, a lower risk of default, and lower interest rates.

Effects on loan risk and interest rate. Everett [2015] looks into the influence of group membership on loan default within 13,486 Prosper loans. They find that the group significantly decreases loan default risk if the group enforces real-life personal connections. Freedman and Jin [2008] find loans with friend endorsements and friend bids have fewer missed payments and yield significantly higher rates of return than other loans. Collier and Hampshire [2010] empirically examine the signals that enhance community reputation in Prosper. They find both structural (e.g., community size) and behavioral community signals (e.g., community endorsements) provide borrowers with lower interest rates.

Effects on loan fundraising. Herrero-Lopez [2009] measures the influence of social interactions in the risk evaluation using a Gaussian mixture model. Their results show that fostering social features increases the chances of getting a loan fully funded, when financial features are not enough to construct a differentiating successful credit request. Horvát et al. [2015] investigate the role of networks within crowds and their performance effects on Prosper, and find that in the early stage of fundraising, network relations provide larger proportions of loans, typically lending four times more per bid than strangers. Similarly, Liu et al. [2015] find that friends of the borrower, especially close offline friends, can promote the loan funding by making leading bids.

In the non-profit platforms (e.g., Kiva), the lending team is another type of social community that is mainly for lenders. Hartley [2010] observes 120 lending teams across 12 group classifications. However, they do not observe these lending teams longitudinally beyond the 2-month observation. In Choo et al. [2014a, 2014b], researchers find that team community of lenders is a very important factor affecting both a lender' selection on loans and promotes micro-finance activities in Kiva.

Additionally, it is worth mentioning that many crowdfunding platforms provide social media sharing features, such as integrations with Twitter and Facebook, to enable the fundraising process. Thus, on these crowdfunding platforms, especially on the reward-based platforms (e.g., Kickstarter), the impact of social media on the crowdfunding campaign is a widely studied problem. For example, Etter et al. [2013] propose a method for predicting the success of Kickstarter campaigns by using both direct information and social features extracted from Twitter. They find that only 4 hours after the launch of a campaign, the predictor with combined features reaches an accuracy of more than 76% (a relative improvement of 4%). Further, Lu et al. [2014] analyze the dynamics of crowdfunding from two aspects: how fundraising activities and promotional activities on social media simultaneously evolve over time, and how the promotion campaigns influence the final outcomes. They observe temporal distribution of customer interest, strong correlations between a crowdfunding project's early promotional activities and the final outcomes, and the importance of concurrent promotion from multiple sources. Hui et al. [2014] identify community efforts to support crowdfunding work, such as providing mentorship to novices, giving feedback on campaign presentation, and building a repository of example projects to serve as models.

3.1.3. Other Sociology Research. Besides the research on platform mechanism and social community, some researchers study the race, region, country or other cultural factors on P2P lending. For example, Pötzsch and Böhme [2010] analyze empirical data of Smava to study the contribution of unstructured, ambiguous, or unverified

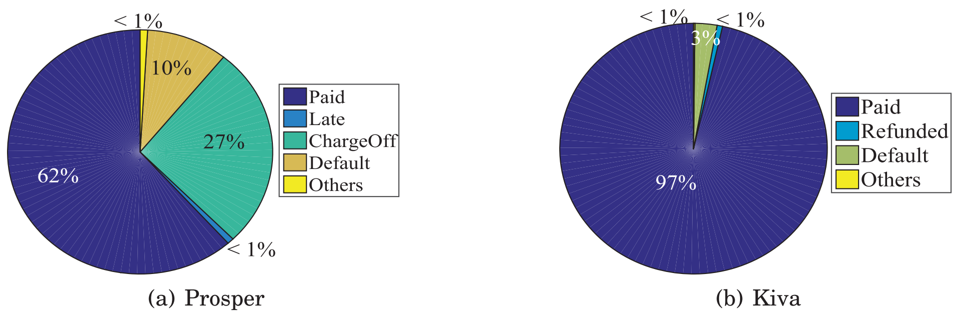


Fig. 4. Statistics of loans with different repayment results.

information to trust building in online social lending. They find that some soft information (e.g., textual statements) actually affects trust building. Pope and Sydnor [2011] analyze discrimination in P2P lending. They examine how lenders in the Prosper market respond to signals of characteristics such as race, age, and gender that are conveyed via pictures and text, and find evidence of significant racial disparities. Duarte et al. [2012] address the question of appearance effects in financial transactions using photographs of potential borrowers in a P2P lending site. They find that borrowers who appear more "trustworthy" have higher probabilities of having their loans funded. Burtch et al. [2013] analyze the cultural differences and geography in online lending using Kiva data. They present evidence that lenders do prefer culturally similar and geographically proximate borrowers. For special crowds, Livingston et al. [2015] present the results of a credit survey given to college students and low-income residents of Tacoma, Washington.

In addition, some researchers make special efforts to compare the P2P lending platforms and industries in different regions. Ashta and Assadi [2009] study different European online micro-lending websites and different models (e.g., Zopa, Smava, Boober, Kokos, and Monetto) using a comparative case study approach. Xu et al. [2015] propose to study a new type of financial fraud of P2P lending in China (i.e., loan request fraud). They think that loan request fraud may be unique to lenders on Chinese P2P lending sites due to the lack of nationwide credit rating systems in China. Chen and Han [2012] conduct a comparative study of online P2P lending practices in the United States and China. They find that lenders in China are more reliable on the "soft information" (e.g., personal relationship, hobby) of borrowers.

3.2. Data-Driven Perspective

Different from the aforementioned research, which studies the problems mainly from the economics and sociology perspective, many scholars and data scientists have conducted extensive data-driven research in P2P lending. They focus on analyzing the massive transaction data for some non-trivial goals. In general, most works are concerned about three specific problems (i.e., *risk assessment*, *fundraising analysis,* and *lending or bidding behavior analysis*). In these works, some statistical and machine learning techniques, such as regressions and optimizations, are widely used.

3.2.1. Risk Assessment. *Risk* or *default* indicates the probability that one loan may not repay the principal and interest to lenders in time. Figure 4 shows some statistics of loans with different repayments on Prosper and Kiva, respectively. From the figure, we can see that about 10% of loans in Prosper and about 3% of loans in Kiva will not repay to the lenders in time. In Kiva, the credit and repaying capability of field partners are much better than borrowers', and there is not any interest rate burden. So lending is much safer than that in Prosper, but there are not any financial profits for lenders. As described in the previous section, risk may be the most important factor that affects the decision making of lenders, especially in profit platforms. Thus, risk assessment is one of the most concerning research problems in P2P lending. The task of risk assessment can be formally defined as a function $\mathcal{R}$:

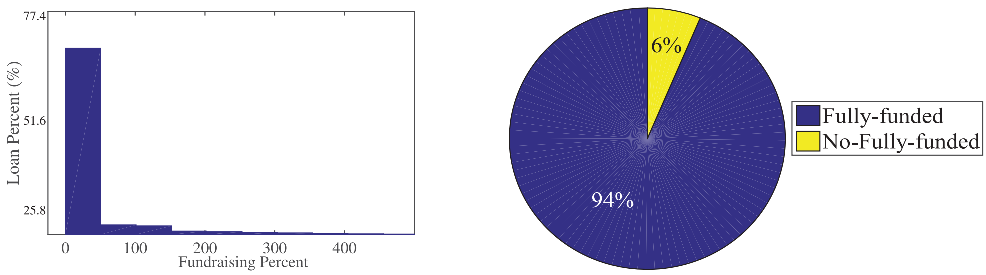
$$\mathcal{R} : \mathcal{M}((f_1^1, \ldots, f_m^1), \ldots, (f_1^n, \ldots, f_m^n)) \longrightarrow (s_1, \ldots, s_n),$$

where $\mathcal{M}$ is a assessment model, f_j^i is the *j-th* feature of loan v_i that is given, and s_i is the estimated score or probability that loan v_i will repay in time. Around the problem of risk assessment, the relevant works can be classified into two groups, that is, one includes those works that attempt to adopt or develop *new assessment models* $\mathcal{M}$ to evaluate the loan risk, the other one includes those works that focus on *extracting new features* f_j^i for better assessment.

Assessment Models. A lot of research has been done for risk assessment models. For instance, Iyer et al. [2009] adopt a regression model to evaluate whether lenders in P2P lending markets are able to use borrower information to infer creditworthiness on Prosper data. They find lenders are able to use available information to infer a third of the variation in creditworthiness that is captured by a borrower's credit score. Besides the regression model, some other conventional classification models from machine learning field are also adopted to assess the loan risk or borrower credit, such as Logistic Regressions [Dong et al. 2010; Zhao et al. 2014; Serrano-Cinca et al. 2015], Support Vector Machine [Wang et al. 2005], Neural Networks [Zang et al. 2014; Byanjankar et al. 2015], Random Forest [Malekipirbazari and Aksakalli 2015], and Gradient Boosting Decision Tree [Zhao et al. 2016b]. In addition, Guo et al. [2016] use an instance-based model and kernel smoothing to assess a "focal" loan's return and credit risk by a voting schema of some past loans. Their experimental results demonstrate the better prediction accuracy of their model compared to the traditional assessment models.

Extracting Features. There are also some relevant studies that are from the perspective of extracting assessment features. For example, Luo et al. [2011] propose a lender composition idea to measure the loans. In their study, they evaluate a being-auctioned loan through the characteristics/features of lenders who have invested to this loan. Serrano-Cinca et al. [2015] find that factors such as loan purpose, annual income, current housing situation, credit history, and indebtedness affect the loan default in LendingClub, and the credit grade assigned by the P2P lending site is the most predictive factor of default. Emekter et al. [2015] also find that higher interest rates charged on the high-risk borrowers are not enough to compensate for higher probability of the loan default. Zhao et al. [2016b] extract various dynamic features from the incremental lenders and temporal situation from the dynamic auction for better risk prediction. Xu et al. [2016] aim at proposing features that may help identify possible fraudulent loan requests during the loan auction process. The results indicate that the proposed feature set (such as *Past Performance, Herding Manipulation*) outperform the baseline features in detecting default loans. Further, Cui et al. [2016] develop a feature selection method to select an optimal subset of features based on the most relevant graph-based features through the Jensen-Shannon divergence measure, for risk evaluation in P2P lending.

3.2.2. Fundraising Analysis. As we described in Section 2.2.4, in many lending-based platforms or crowdfunding with fixed goals, only the transactions on the loans that can receive enough bids or pledges in time are effective; otherwise, all the investment transactions will fail and be canceled (i.e., following the "all-or-nothing" principle). Figure 5 shows the percent of loans with different fundraising results on Prosper and



(a) Prosper (b) Kiva

Fig. 5. Statistics of loans with different funding results.

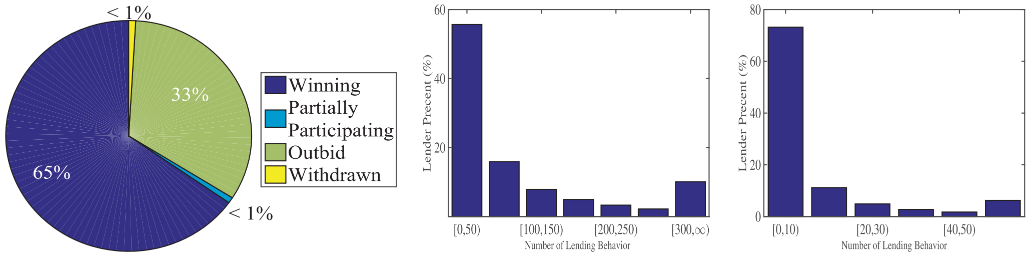
Kiva, respectively. From the figure, we can see that less than 25% of loans in Prosper and 94% of loans in Kiva will receive enough money in time (raising more than 100%). Due to the auction trading rule in Prosper or other profit platforms, some loans may raise more than 100% bids. The average auction duration in Prosper is 7.58 days, whereas the fundraising time for loans in Kiva is much longer (e.g., several months). Thus, loans in Kiva are much more likely to be fully funded. In the profit lending platforms, predicting the fully fund possibilities of loans is another important problem that can be formalized by a function $\mathcal{F}$:

$$\mathcal{F} : \mathcal{M}'((f'^{1}_{1}, \ldots, f'^{1}_{m}), \ldots, (f'^{n}_{1}, \ldots, f'^{n}_{m})) \longrightarrow (s'_1, \ldots, s'_n),$$

where $\mathcal{M}'$ is a model for predicting the loan success, f'^{i}_{j} is the *j-th* feature of the given loan v_i and s'_i is the estimated score or probability that loan v_i will receive enough lending in time. Besides the fully fund prediction problem in profit platforms, in the non-profit platforms (e.g., Kiva), the dynamics and efficiency of fundraising are also well studied. The research on fundraising analysis may vary a lot in different types of platforms due to the different working mechanisms of these platforms. Thus, we organize these research works based on different platform types in the following.

In profit lending platforms. For the fundraising analysis, some research works focus on the typical profit P2P lending platforms. For example, Ryan et al. [2007] propose two regression models combining personal and social determinants (e.g., endorsement, listing profile, group) and financial determinants (e.g., credit grade, debt to income) for fundraising percent and number of bids, respectively. The most interesting finding in their study are the significant effects of *Group Leader Endorsements* on both funding percentage and the number of bids. Herzenstein et al. [2008] studies both the borrower-related determinants (e.g., race, gender, credit) and loan-related determinants (e.g., loan amount, interest rate, auction duration of loan) of fundraising success in Prosper with a Logistic Regression. Their results indicate that borrower-related financial determinants, especially credit grade, affect fundraising results the most, while loan-related variables mediate affect the likelihood of fundraising success. Zhang et al. [2016a] study the collective evolution inference in P2P lending network, that is, how the financial activities of different loan listings can evolve over their entire fund-raising periods. Zhao et al. [2017] formalize the fundraising of loans as a problem of market state modeling and propose a sequential approach with a Bayesian hidden Markov model for that.

In non-profit lending platforms. Instead of interest rate or profit, one loan's purpose or motive is a more important factor affecting its fundraising in the non-profit lending-based platforms. For example, in Kiva, the description of borrowing money



(a) Bidding results in Prosper (b) Lending statistics in Prosper (c) Lending statistics in Kiva

Fig. 6. Statistics of lending behavior.

is important for a borrower or field partner to solicit donations. Of course, the field partner's profiles (especially the credit) of the loan are also very important to affect the lenders' decisions. Ly and Mason [2010] study the impact of publicly visible project characteristics on fundraising dynamics in Kiva. Their results indicate that smaller loans, groups, and women get funded faster, as do loans to sectors of activity with low entry costs. Ly and Mason [2012] empirically investigate the effect of competition between microfinance organizations seeking subsidized capital from individual social investors. Using Kiva data, they find that competition has a sizable negative impact on projects' funding speeds, and the effect is stronger between close substitutes. In Kiva, the fundraising dynamics of loans will affect the field partners' following activities because the funding money is used to backfill their capitals.

Additionally, in the reward-based crowdfunding platforms, the fundraising dynamic of campaigns is also widely studied, especially for campaigns with fixed goals. For example, Mollick [2014] offers a description of the underlying dynamics of success and failure among crowdfunded ventures with a survival analysis method. They suggest that personal networks and underlying project quality are associated with the success of crowdfunding efforts and that geography is related to both the type of projects proposed and successful fundraising. Mitra and Gilbert [2014] explore the factors that lead to successfully funding a crowdfunding project. They find the language used in the project has a surprising predictive power accounting for 58.56% of the variance around successful funding. Solomon et al. [2015] conduct an experimental simulation of a crowdfunding website to explore timing affects coordination of crowdfunding donations. They find that making an early donation is usually a better strategy for donors because the amount of donations made early in a project's campaign is often the only difference between that project being funded or not. Li et al. [2016] develops a censored regression approach where one can perform regression in the presence of partial information. The proposed model performs significantly better at predicting the success of future projects. Besides, in the crowdfunding platforms, there is also extensive research that makes efforts on promoting the fundraising of campaigns from the human-computer interaction perspective, such as Gerber et al. [2012], Gerber and Hui [2013], Greenberg and Gerber [2014], and Xu et al. [2014].

3.2.3. Lending or Bidding Behavior. Besides the risk assessment and fundraising analysis, some researchers also study the lenders' lending behaviors from a data-driven perspective. Lending behaviors can reflect the lender psychology, and even the dynamics of fundraising and the whole market state [Zhao et al. 2017]. Figure 6 shows some statistical results of bidding or lending behaviors in Prosper and Kiva. Since Kiva does not adopt an auction and bidding mechanism, there are no corresponding results of bidding. From Figure 6(a), we can see that about 33% of bids will outbid and fail due to the serious competition on a small number of popular loans. In both Prosper and Kiva, most lenders have small numbers of lending behaviors. Lenders in Prosper are more active, with higher lending frequencies than lenders in Kiva.

Around the lending behavior analysis, there are also some specific research problems such as the *decision making* of lenders. Wan et al. [2016] explore lenders' decision-making processes in P2P lending platforms in China by drawing on trust theory and an integrated decision-making model. They find that the initial trust plays a critical role in determining a lender's willingness to lend but has little impact on mitigating lenders' fear of borrower opportunism. Chen et al. [2016] address the research on investor decision-making behaviors in P2P lending from the perspective of rationality and sensibility. They observe that there is an inverted-U relationship between social distance and bidding amount that determines whether rationality or sensibility dominate investors' decisions. In Rajaratnam et al. [2016], the authors show how observation of early decisions in a sequence can be informative about later decisions and can, when coupled with a type of adverse selection, also inform credit risk. Hoegen et al. [2017] conduct a systematic and interdisciplinary literature review to examine which factors influence investment decision making in crowdfunding. They find a higher impact of social capital in crowdfunding than that in traditional investments such as venture capital.

Besides the research focusing on decision making of lenders, some researchers also analyze the *dynamics of lending behavior,* which is often formalized as a sequence problem $\mathcal{S} : (o_1^i, \dots o_t^i, \dots, o_T^i)$, where o_t^i is the observation variable at time t on loan v_i. In the literature, observation variables are often constructed by the temporal lending/bidding amount or the number of lenders on a loan [Zhao et al. 2017]. The dynamics of lending behavior may vary a lot in different platforms, so we organize this research on the dynamics of lending behavior according to platforms with different trading rules.

In auction-based platforms. In these platforms, due to the auction and bidding, some loans will receive several time more investment bids than their request amount with *herding* phenomenon occurring. As a special phenomenon of lending behaviors, herding is widely studied. Shen et al. [2010] propose a model based on preferential attachment and fragmentation to model the bidding behavior of lenders on Prosper. Their data analysis presents strong empirical evidence that there are significant *herding* effects when lenders made their investment decisions. Ceyhan et al. [2011] investigate the change of various attributes of loan requesting listings over time, such as the interest rate and the number of bids. They also observe that there is herding behavior during bidding, and for most of the listings, herding occurs at very similar time points (e.g., more likely to occur at the beginning and end of loans' durations). Furthermore, Herzenstein et al. [2011] provide evidence of strategic herding behavior by lenders such that they have a greater likelihood of bidding on an auction with more bids (a 1% increase in the number of bids increases the likelihood of an additional bid by 15%). In Luo and Lin [2013], the authors design a decision tree to model the formation of herding during the decision making of lenders. Their study finds that when herding behavior arises, lenders follow the behaviors of other lenders and generally ignore their own information, which might cost them too much to obtain or analyze. Lee and Lee [2012] empirically investigate herding behavior in one of the largest P2P lending platforms in Korea and find strong evidence of herding and its diminishing marginal effect as bidding advances. Liu and Xia [2017] use evolutionary game methodology to analyze online P2P lending behavior and explore P2P fund success from the dual perspective of lenders and borrowers.

In fundraising-based platforms. Similar to the herding in P2P lending, there is a similar phenomenon in the fundraising of campaigns in the fundraising-based platforms. Kuppuswamy and Bayus [2014] empirically study the dynamics of backers over the campaign funding cycle and find there is a U-shaped pattern of backers' supports, that is, backers are more likely to contribute to a project in the first and last week as compared to the middle period of the funding cycle. The similar result is also observed in Lu et al. [2014].

3.2.4. Other Data-Driven Research. Besides the aforementioned research issues in P2P lending, researchers have also studied some other interesting tasks (e.g., loan classification, loan recommendation) by deeply exploring the P2P lending transaction data. For instance, Liu et al. [2012] study the problem of classifying user motivation statements from Kiva by SVM-based classifiers. They find that lenders belonging to any team(s) make 0.78 more loans and lend $31 more per month than those without team affiliations. Similarly, Bretschneider and Leimeister [2017] conduct an empirical study to describe backers' motivation in crowdfunding. Results indicate that backers indeed have several self-interest motivations for funding (e.g., prospect of a reward, expectation of recognition from others). Lee et al. [2015] propose a fairness-aware loan recommendation system for social welfare, optimizing accuracy and fairness altogether based on one-class collaborative-filtering techniques for charity and micro-loan platforms (i.e., Kiva). Zhao et al. [2014] also study the loan recommendation problem in P2P lending. In their study, they propose to manage risk through integrating portfolio theory into a personalized recommendation technique (i.e., collaborative filtering). Zhang et al. [2016b] modify the traditional personalized recommendation by the surplus maximization, which can be applied to P2P lending. The results suggest their method compares very favorably to currently popular methods. Zhao et al. [2016b] study the problem of loan portfolio selection in P2P lending in which a multi-objective selection strategy (considering the loan risk, fully funded probability, and winning-bid probability synchronously) is proposed. In crowdfunding platforms, An et al. [2014] and Rakesh et al. [2015] study the problem of recommending investors or backers to projects by integrating statistical techniques into a recommendation framework. Rakesh et al. [2016] propose a probabilistic recommendation model, called CrowdRec, that recommends Kickstarter projects to a group of investors by incorporating both the on-going status of projects and the personal preference of individual members. However, these personalization studies in P2P lending are still open and being explored.

4. PROSPECTS

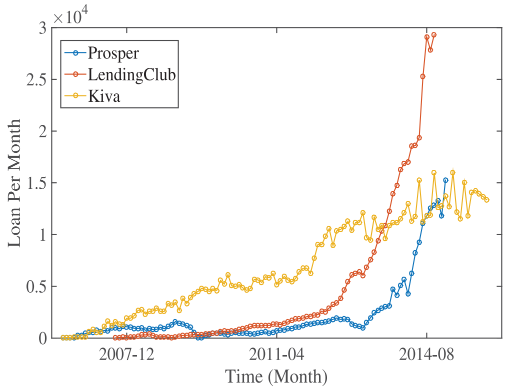
In the previous sections, we summarize P2P lending platforms and review recent advances in this field. In this section, we will discuss the prospects of P2P lending with the transaction data collected from Prosper, LendingClub, and Kiva and suggest several future research directions.

4.1. Analysis and Industry Prospects

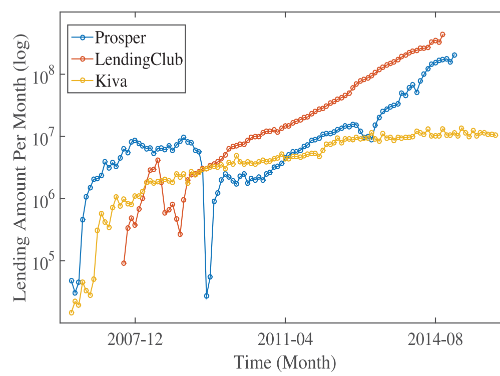
We collect the monthly loans that successfully raised enough money and the amount of lending money on these loans from three representative platforms (i.e., Prosper, LendingClub, and Kiva). We have obtained all transaction information from the first month of each platform to September 2015. We show the monthly funded loan amount and lending amount on these platforms in Figure 7.

From these the figure, we can see the following.

—*Amount.* By August 2014, the number of successful loans per month in three platforms is more than 13,000 (Prosper), 29,000 (LendingClub), and 12,000 (Kiva). The lending money amount per month is more than $176 million (Prosper), $433 million (LendingClub), and $10.5 million (Kiva). The volume of monthly amount reflects the prosperity of P2P lending. Also, the average raising amount per loan is $13,276 (Prosper), $11,776 (LendingClub), and $871 (Kiva), in which the loan average is similar in Prosper and LendingClub and much larger in Kiva. This happens because



(a) Funded loan statistics.



(b) Lending amount statistics.

Fig. 7. Statistics of transaction amount in Prosper, LendingClub, and Kiva.

Prosper and LendingClub are typical profit P2P lending platforms, whereas Kiva is a non-profit platform where lenders lend money without receiving any interest or profit to borrowers whose request amount is much smaller.

—*Trend*. From the starting days of three platforms to September 2015, the transactions in these platforms are increasing rapidly. The successful loans and lending money amount are increasing exponentially in Prosper and LendingClub, especially in LendingClub. Relatively speaking, the growth of Kiva is stable.

—*Trough*. In Figure7(b), there are two obvious troughs in the plots of Prosper and LendingClub between December 2007 and August 2009. The possible reason may be the bad macro-economic environment during this time. As reported in Demyanyk and Van Hemert [2011] and Purnanandam [2011], the United States broke out a nationwide *subprime mortgage crisis* betweem December 2007 and June 2009. The typical profit platforms (e.g., Prosper and LendingClub) are generally treated as a kind of wealth-management service by individuals, and lenders lend money to others for making money. Thus, the transactions in Prosper and LendingClub are significantly affected. On the contrary, in the non-profit platforms (e.g., Kiva), lenders cannot receive any interest or extra money except their principals from the borrowers. Thus, transactions in Kiva are not significantly affected by the macro-economic environment.

From the aforementioned analysis, recent years have witnessed the rapid development of P2P lending. Especially after December 2012, the growth begins to accelerate sharply. Considering the development tendency of P2P lending in recent years and the current economic environment, the P2P lending market will have better prospects in the future. More specifically, we plot the adjust annualized return of each quarter in LendingClub from "2010-Q1" to "2016-Q4" in Figure 8. The labels in the legend, such as "A" (highest) and "FG" (lowest), are the credit ratings that LendingClub uses to evaluate the borrowers and loans. We can see that loans with different credits may bring different returns, such as "A" loans have low but stable returns, whereas "FG" loans fluctuate seriously but may have the highest returns. On the whole, most investors can gain 5% to 10% profits. It is worth noting that the return has grown significantly in the latest year.

4.2. Possible Research Directions

In Section 3, we reviewed the recent advances on P2P lending. Although extensive research has been done, there are still some critical problems in this field. With the

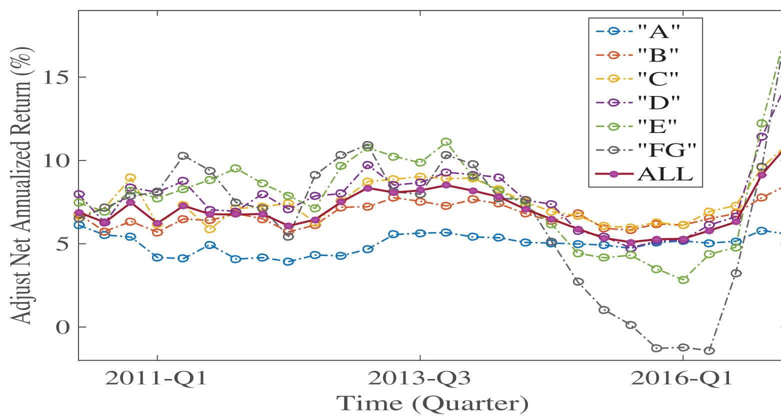


Fig. 8. Adjust annualized return in LendingClub.

rapid development of P2P lending, this field will attract more researchers' attention. In this subsection, we introduce our opinions on several open problems for further research extensions.

4.2.1. Pricing. Pricing is the process whereby a business sets the price at which it will sell its products and services. For loans, pricing is to determine a reasonable interest rate based on the borrowers' credits and other information. In P2P lending, pricing loans reasonably has great positive effects on loan fundraising and repayment and is important for both borrowers and lenders.

In traditional marketing, pricing strategy is a key variable and widely studied (e.g., value-based pricing [Hinterhuber 2004], marginal cost pricing [Baumol and Bradford 1970], etc.). There is also extensive research on the pricing for bank loans [Greenbaum et al. 1989; Stein 2005]. For instance, risk-based pricing [White 2004; Edelberg 2006] is a methodology widely adopted by lenders in the mortgage and financial services industries. Risk-based pricing has been in use for many years as lenders try to estimate loan risk in terms of interest rates. The interest rate on a loan is determined not only by the time value of money but also by the lender's estimate of the probability that the borrower will default on the loan. According to this pricing theory, a borrower who the lender thinks is less likely to default will be offered a better/lower interest rate. Borrowers who are safer should be more likely to borrow and repay [Simkovic 2013]. However, the corresponding research of pricing for online micro-finance loans or P2P lending is still lacking.

Actually, the pricing used by most P2P lending platforms currently is based on the risk-based pricing theory. Berger and Gleisner [2009] and Emekter et al. [2015] report the detailed statistics on loan rates and borrowers' credits in Prosper and LendingClub, respectively. Generally speaking, borrowers with worse credits must pay more (higher interest rates) for their loans. However, the problem of pricing for loans in P2P lending is still being explored, for instance, how to price loans from the borrower perspective (i.e., pricing for maximizing the fully funded probability and minimizing the default probability) and the lender perspective (i.e., pricing for maximizing the profit); how to consider the fairness of borrowers and lenders when pricing loans; and how to help lenders dynamically bid with optimal prices in the loan auction. These research extensions are all interesting and challenging.

4.2.2. Mechanism Improvement. Since P2P lending is a recently emerging market, the mechanism has been developing and improving. These studies focus on the improvements of the trading rules (e.g., auction, incentive) and lending or funding option (e.g., amount, reward) setting. For example, Wei and Lin [2016] compare two representative mechanisms in P2P lending (i.e., auctions and posted prices). They find that under platform-mandated posted prices, loans are funded with higher probability, but the preset interest rates are higher than borrowers' starting interest rates and contract interest rates in auctions. In this direction, more studies are needed for more efficient trading rules. Besides, from the view of platforms, there are many other rooms on the improvement of mechanism. For example, in some platforms, such as Kiva, optimizing the funding option settings (e.g., $ 50, $100, $150) is also an open problem. Besides, how to manage the market and roles/participants dynamically and promptly is also worth exploring.

4.2.3. Risk Management. Although many researchers have focused their attentions on assessing the risk for loans in P2P lending, as reported in Section 3.2.1, this problem is still critical. For LendingClub, as reported by Serrano-Cinca et al. [2015] or LendingClub herself,[22] the average loan default rate is about 5% to 10%, which is relatively higher than that of traditional business loans.

From our point of view, for better managing risk, platforms should optimize their mechanisms from platform management, enhancing the role of lending community. For instance, Renrendai charges fees from all borrowers to fill the loss provision account. Evaluating loans or borrowers by lenders is also an effective method [Klafft 2008a; Luo et al. 2011]. With the development of P2P lending, massive long-term and multiple-loan data of loyal customers (borrowers) should also be well studied for evaluating or managing risk. Besides evaluating risk using the borrowers' social information, exploiting some external real information or the knowledge of other customers especially the lenders are all possible solutions.

4.2.4. Privacy. In P2P lending markets, many borrowers disclose more personal data in order to get better credit ratings and speed up their fundraising. As we reported in Section 3.1, race, photographs, and stories all affect the fundraising on both profit platforms and non-profit platforms. However, as claimed in Böhme and Pötzsch [2010], there is a conflict between economic interests and privacy goals in P2P lending, and it is simply not worth disclosing personal details. Nowadays, privacy issues have been paid more and more attention in many domains, such as in social networks [Gross and Acquisti 2005], mobile services [Gedik and Liu 2005], and data mining [Li et al. 2012]. However, there is still a lack of particular research on privacy protection in P2P lending. Especially, protecting privacy without declining the borrowers' profits is a challenging problem. Besides, trustworthiness and fraud should be studied in particular, which are also very important factors in privacy and risk management.

4.2.5. Personalization. Personalization is another promising direction for research extensions in P2P lending. Generally, personalization is the process of enhancing customer service by understanding individual users' characteristics or preferences. Personalization is a mean of meeting the customer's needs more effectively and efficiently, consequently, increasing customer satisfaction and the likelihood of repeat visits. In many domains, the personalization has been widely used and well-studied, such as web personalization [Mobasher et al. 2000; Eirinaki and Vazirgiannis 2003], personalized search [Qiu and Cho 2006; Dou et al. 2007], and personalized recommender systems [Resnick and Varian 1997; Adomavicius and Tuzhilin 2005; Liu et al. 2011]. Personalization is also important but still underexplored in P2P lending. Zhao et al. [2014] propose to make personalized loan recommendations for lenders by considering

[22]https://www.lendingclub.com/info/demand-and-credit-profile.action.

lenders' personal preference and reducing the loan risk simultaneously. Also, some platforms such as Prosper and LendingClub allow lenders to explore loans with the criterions on rate set by lenders themselves [Zhao et al. 2016b]. However, there is still a long way to personalization service in P2P lending.

In our opinion, some specific possible research extensions on personalization in P2P lending can be summarized as follows.

—*Personalization for borrowers.* For borrowers, platforms can provide personalized services such as: (1) recommending social communities (e.g., group in Prosper) and (2) seeking lenders for each borrower who are most likely to lend to this borrower.
—*Personalization for lenders.* For lenders, platforms can provide personalized services such as: (1) recommending social communities (e.g., group in Prosper and team in Kiva); (2) providing personalized search results (e.g., loans, etc.) based on lenders' preferences; and (3) recommending personalized loans to each lender. Recommending loans to lenders may consider both the lender's preference and the loan characteristics (e.g., risk and credit). Besides, recommending personalized portfolio rather than single loans is another further task.
—*Personalization for communities.* For communities, platforms can provide personalized services from tailoring community pages and recommending customers (e.g., borrowers or lenders). Besides, in the previous work [Choo et al. 2014a, 2014b], researchers find that many lenders in a team may lend to the same loans sometimes, and team community is a very important factor that affects both a lender's selection and decision about loans and promotes micro-finance activities in Kiva. Thus, recommending loans to an entire community is also an interesting problem [Rakesh et al. 2016]. In fact, this is also a challenging problem in traditional recommender systems named *group recommendation* [Jameson and Smyth 2007; Amer-Yahia et al. 2009; Zhao et al. 2016a].

5. CONCLUSIONS

In this article, we provided a comprehensive survey on P2P lending. Specifically, we summarized some mainstream P2P lending platforms in the world and provided a systematic taxonomy for them. In the meantime, we compared different types of working mechanisms in details. We also reviewed and organized the recent advances on P2P lending from multiple aspects. However, there are still some critical challenges and open problems in this field that need to be solved. Thus, we suggested several future research directions, including the pricing problem, mechanism improvement, risk management, privacy preserving, and personalization. We hope future research works will advance P2P lending and bring more intelligent, secure, and efficient services and platforms.

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