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The value of financial intermediation: Evidence from online debt crowdfunding☆

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ABSTRACT

Most online marketplaces are peer-to-peer. Credit ones, however, are not and they have resurrected many features of traditional financial intermediaries. To understand why, we use online credit as a laboratory to investigate the value of financial intermediation. We develop a structural model of online debt crowdfunding and estimate it on a novel database. We find that abandoning the peer-to-peer paradigm raises lender surplus, platform profits, and credit provision, but exposes investors to liquidity risk. A counterfactual where the platform resembles a bank by bearing liquidity risk can generate larger lender surplus and credit provision when liquidity is low and lenders are risk averse.

1. Introduction

Many online marketplaces, such as Uber, Airbnb, and eBay, operate on a peer-to-peer paradigm focused on matching buyers with sellers. In the early days, online credit marketplaces — commonly known as debt crowdfunding platforms — adopted a similar approach, where individual lenders would fund specific loans, holding them until maturity. This peer-to-peer setup has since evolved. Most debt crowdfunding platforms now operate under a "marketplace credit" paradigm, where they aggregate loans into portfolios that are sold to investors, eliminating the need for investors to select loans individually. Because the portfolios often have shorter maturities than the underlying loans, the maturity mismatch introduces liquidity risk, i.e., the risk associated with the need to refinance the loans when the portfolio matures. Under the marketplace credit paradigm, investors have borne liquidity risk; yet many platforms have recently begun offering "bank-like" products that resemble traditional deposits, thereby shifting the liquidity risk onto the platforms themselves.

We ask why online credit evolved differently from other online marketplaces, and what is the welfare value of its unique features. These questions are important, because online debt crowdfunding is an increasingly large investment and consumer credit channel (Rau, 2020). Moreover, it provides a clean environment to quantify the welfare value of financial intermediation in general as, in comparison to traditional intermediaries, it is exclusively focused on intermediating

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credit and it is less exposed to the potential confounding impact of regulation (Buchak et al., 2018).

To address our questions, we build and estimate a structural equilibrium model of online debt crowdfunding that rationalizes its development. The key forces in our model are maturity mismatch and liquidity risk. By funding longer-maturity loans while also allowing lenders to liquidate their investments in the short term, the loan portfolios offered under the marketplace and bank-like credit paradigms increase credit provision and create value for lenders, borrowers, and the platform itself. However, the extent to which marketplace credit and bank-like credit generate value varies based on liquidity risk and how much investors are willing to tolerate it.

We estimate our model on a novel, hand-collected micro database of the universe of loan applications, actual loans, and loan portfolios on a leading Chinese online debt crowdfunding platform, Renrendai. During our sample period, Renrendai both sold loan portfolios to investors bearing liquidity risk (under the marketplace paradigm) and allowed direct investment in loans (under the peer-to-peer paradigm). The data show lenders' investment choices: whether they invest directly or buy a portfolio product, and which portfolios they choose if they opt for the latter. We can match this information with the maturity of the loans in the portfolios products, and thus compute a precise measure of maturity mismatch. Renrendai, moreover, allows lenders who do not want to roll over their portfolio investments to sell the underlying loans on its internal secondary market. Our data contain every transaction in the primary and secondary markets, and reveal how fast a loan is resold, thus quantifying its liquidity.

Our main findings are as follows. First, similar to online credit platforms in the U.S. and other countries, we observe the transition from peer-to-peer to marketplace credit. In 2010, when Renrendai was launched, 100% of lending was peer-to-peer; but by the end of our sample in early 2017, over 98% of the loans on Renrendai are funded as part of a marketplace loan portfolio. The key feature of these portfolios is maturity mismatch: whereas their most common maturities are 3, 6, and 12 months, the underlying loans typically mature in 36 months. This exposes the lenders to non-trivial liquidity risk. Moreover, lender investments have become more diversified and less exposed to defaults, especially for portfolio products purchased on the platform, consistent with a change in the platform's clientele towards investors that are more averse to risk.

Second, the estimates of our structural model shed light on lender preferences for loan and portfolio product characteristics, as well as on the platform's preferences for individual loan attributes when assembling portfolios. Lenders prefer higher returns, especially for peer-to-peer loans, and portfolio products with lower liquidity risk (shorter resale time on the secondary market). Moreover, lender preferences are heterogeneous: the more sophisticated, active lenders have a stronger preference for yield and a weaker disutility from liquidity risk, whereas the opposite is true for less frequent investors.

Third, we combine our estimates of the lender demand model with a platform profit function to simulate counterfactuals. We compare the baseline marketplace credit with two counterfactual scenarios: peer-to-peer credit, where only direct lending is allowed, and bank-like credit, where the platform sells portfolio products but bears liquidity risk. In the marketplace and bank-like scenarios, the platform maximizes profits by choosing portfolio product target return, the mismatch between portfolio duration and the maturity of the underlying loans, and the resale time of portfolio loans on the secondary market. Marketplace credit appears welfare-improving relative to the peer-to-peer paradigm: the counterfactual allowing only direct lending generates a 73% drop in credit provision and a 45% decline in lender surplus. We find that this is driven by the fact that under the marketplace paradigm, maturity mismatch allows the platform to offer a broader assortment of portfolios, more closely tailored to the lenders' maturity preferences; on the other hand, the platform's ability to search, screen, and monitor borrowers plays a lesser role. We also find that, when the platform's cost of generating liquidity is low—i.e., it can easily repurchase loans for its portfolio products without bearing significant costs, bank-like credit yields similar outcomes to marketplace credit, with only a small drop in platform profits (0.2%).

That comparison is different, however, when we raise the platform's cost of generating liquid loans. Under higher liquidity costs, relative to bank-like credit, the marketplace paradigm exhibits lower credit provision and lender surplus, but higher platform profits. In other words, when liquidity is low marketplace credit is preferable from the platform's point of view, but worse for lenders and borrowers. Finally, in counterfactuals where the lenders have weaker utility from yields and stronger disutility from liquidity risk, the bank-like paradigm is a Pareto improvement, raising platform profits too.

These results are consistent with a narrative in which, in the early days of online debt crowdfunding, the platform mainly attracts risk-tolerant lenders, who seek higher returns and have higher welfare under the peer-to-peer and marketplace paradigms. As the platform's clientele grows, it comes to encompass more risk-averse lenders, who are more sensitive to liquidity risk and have higher welfare under bank-like credit. Our findings are in line with anecdotal evidence about the most mature platforms such as LendingClub, Funding Circle, RateSetter, or Zopa, which have shut down peer-to-peer credit, offering instead securitized (marketplace) loan portfolios to a more risk-tolerant institutional investor clientele as well as, in recent years, traditional banking products to more risk-averse retail investors.

Our paper makes three main contributions. First, it contributes to the literature on the value of financial intermediation. Since the seminal work of Diamond and Dybvig (1983), the theory of financial intermediation points to maturity transformation as a central tool to facilitate the provision of credit for longer-term investment. Empirical work in this literature has used bank-level data to develop liquidity risk indexes (Berger and Bouwman, 2009; Brunnermeier et al., 2012; Bai et al., 2018; Ma et al., 2020) and has estimated the costs and benefits of maturity transformation (Fuster et al., 2017; Segura and Suarez, 2017; Drechsler et al., 2021), focusing on the relation between liquidity risk and financial stability. We also measure liquidity risk; but our focus is different, as we study how it affects credit provision and welfare. With our detailed data, we can construct a precise measure of liquidity risk both at the individual loan and portfolio product level and estimate lenders' preferences. We are also able to simulate a rich set of counterfactual scenarios, illustrating potential conflicts of interest of the platform vis-à-vis lenders and borrowers. In addition, online debt crowdfunding constitutes a comparatively clean and tractable setting, as its business model is entirely focused on intermediating loans, and, during our sample period, it was less exposed to the potential confounding impact of regulation (Buchak et al., 2018).

Second, our paper provides new results on the design of online debt crowdfunding platforms. Much of the literature has focused on the information aspects of platform design: information provision to investors (Vallée and Zeng, 2019), efficiency of pricing mechanisms (Franks et al., 2021), and the welfare losses associated with asymmetric information (Kawai et al., 2022; DeFusco et al., 2022). We take a different, complementary angle. Building on the evidence that online credit platforms increasingly offer a combination of marketplace loan portfolios and traditional bank-like products, we focus on maturity mismatch and liquidity risk, and their impact on welfare. In that respect we also relate to the literature comparing online and offline credit intermediaries (Buchak et al., 2018; de Roure et al., 2022), as well as to the industrial organization literature on online marketplaces reviewed by Einav et al. (2016). Our results help rationalize the evolution of the design of online debt crowdfunding platforms from peer-to-peer to a combination of marketplace and bank-like credit.

Third, our paper contributes to the literature on structural estimation in financial intermediation (Egan et al., 2017; Crawford et al., 2018; Wang et al., 2022), online credit (Kawai et al., 2022; Xin, 2020; Tang, 2020; DeFusco et al., 2022), and online marketplaces in general (Dinerstein et al., 2018; Einav et al., 2018; Fréchette et al., 2019; Farronato and Fradkin, 2022). Work in this literature has so far focused on buyers and sellers or lenders and borrowers, placing less emphasis on an active role for platforms. In contrast, our approach directly models the design of portfolio products by the platform.

2. Institutional background, data, and descriptive evidence

2.1. Development of the business model of online debt crowdfunding

China, the U.S., and the U.K. are the largest markets for online credit, accounting for about two-thirds of total lending volume (Cornelli et al., 2020). Over 2014–2019, online credit accounted for about 7.5% of total consumer credit in China.[1]

Initially, online credit platforms operated solely through direct, peer-to-peer lending, where lenders selected and held loans until maturity. Over time, two key innovations emerged: platforms began offering portfolio products, often assembled by robo-advisors, and established secondary markets where loans could be traded before maturity. These features define a new "marketplace credit" paradigm of online debt crowdfunding. Marketplace credit enables maturity mismatch in portfolio products, allowing them to include longer-term loans that can be resold on the secondary market when the portfolio matures. A defining aspect of this paradigm is that investors bear liquidity risk, meaning they might have to sell at a discount or wait longer to liquidate their investments. In the U.S., LendingClub introduced a secondary market for loans in 2008 and Prosper in 2009; in the U.K., Funding circle, RateSetter, and Zopa opened a secondary market in 2010, whereas in continental Europe, Bondora launched it in 2013. Virtually every Chinese online credit platform offered portfolio products and set up secondary markets shortly after their establishment.

More recently, many online credit platforms have increased their reach to retail investors by selling bank-like savings products. In bank-like products, the investor can liquidate at any time, but the intermediary bears the liquidity risk. The platform still provides marketplace portfolio products, but they are targeted to institutional investors. For instance, in 2021 LendingClub acquired Radius Bank and started to offer deposit services to retail investors; but at the same time, institutional investors on LendingClub can still invest in portfolio products where they bear the liquidity risk.

Online debt crowdfunding in China experienced a similar evolution despite recently undergoing a restructuring driven by regulation. A number of platforms have shut down, and others have become "loan aid agencies" selling services to traditional intermediaries. However, several Chinese platforms that continue to operate offer bank-like products. For instance, in 2019 FinVolution (formerly Paipaidai) acquired a 4.99% stake in Fujian Strait Bank and formed an alliance with the bank focused on consumer lending, and 9fgroup Tech invested in Hubei Consumer Finance Company through its wholly-owned subsidiary; in 2023, Lufax Holding announced its acquisition of Ping An OneConnect Bank (Hong Kong) Limited.[2] Despite the regulatory tightening, Chinese online credit companies continue to pursue bank-like activities through alliances, acquisitions, and by shifting their focus to Hong Kong.

[1] Source: Elaborated from data from the Wang Dai Zhi Jia webpage.

[2] "FinVolution acquires stake in Fujian Strait Bank", *Sina Finance*, 19 December 2019; "Lufax Holding achieved operating income of 6.964 billion yuan in the first quarter of this year", *Shanghai Securities News*, 23 April 2024.

2.2. Renrendai

We base our analysis on a novel, hand-collected database covering the universe of loan applications and credit outcomes on debt crowdfunding platform Renrendai (人人贷). During our sample period, Renrendai was the fifth largest player in the sector in China, and as of 2019 it had a 5% market share.[3] Between its launch in 2010 and the end of our sample period in February 2017, Renrendai had a cumulative turnover of ¥25 bn ($3.7 bn) and registered over 1 million active users between borrower and lender accounts.

During our sample period, Renrendai is representative of a typical debt crowdfunding platform as it operates like most online credit platforms in China as well as other countries. In Renrendai, users can be borrowers or lenders. Borrowers pay a small participation fee to apply for a loan on the platform.[4] When submitting a loan application, a prospective borrower specifies the amount she seeks, and proposes an interest rate and maturity. Renrendai pre-screens loan applications, assigning a credit rating to borrowers. Following this step, loan applications become visible to prospective lenders, and are available on Renrendai's platform for one week. If an application is not fully funded within that time window, it is considered unsuccessful and it is turned down; Renrendai then removes the application from its website and the borrower does not receive the funds she requested.

Lenders pay no fees and can invest on Renrendai via two channels: direct (peer-to-peer) credit, where the lender selects the individual loans she intends to fund, and marketplace credit, where the platform sells the lender a share in a diversified portfolio of loans. Marketplace lenders can choose from a menu of portfolios known as Uplan (UU计划). Renrendai offers every day a new set of Uplan portfolios, differentiated by target annual return (ranging between 6% and 11%), maturity (between 3 and 24 months), and minimum investment amount (¥1000 or ¥10,000). At maturity, Uplan lenders can roll their investment over or liquidate it. If they liquidate, the platform places the underlying loans on the secondary market, and does not bear the liquidity risk: the lenders do not receive a payment until all the corresponding loans have been resold. The loan is sold "at par", i.e., at a fixed price of ¥1 for each ¥ loaned. As the price does not adjust to market conditions, the seller may not be able to find immediately a buyer and might be forced to wait before disposing of the loan. Renrendai makes a profit on Uplan based on the spread between the interest payments it receives on the underlying loans and the returns it pays to the lenders.

Fig. 1 breaks down credit at Renrendai during our sample period between direct and marketplace loans. When Renrendai was first launched, online debt crowdfunding was based on the older peer-to-peer paradigm, and 100% of loans were direct. Portfolio investment was introduced in December 2012, and since then we observe a steady rise of marketplace credit, reaching 98% of total investment at the end of our sample period in February 2017. We build on this stylized fact, and investigate the welfare effects of the marketplace credit model in comparison to alternative platform designs. In October 2020, regulatory pressure to limit online lending led to withdrawals and low liquidity in Renrendai's secondary market. Since this happened more than three years after our sample period, it is unlikely that loans from before March 2017 are the root of these developments.[5]

[3] "China's Renrendai sees future in SMEs as P2P industry reels", *Financial Times*, 7 January 2019.

[4] There are no detailed data on these fees, which implies that we cannot explicitly include them in our analysis. However, this is unlikely an issue as they have been constant over the sample period and across borrowers, and very small in magnitude.

[5] The available evidence from industry regulatory bodies such as the National Internet Finance Registration and Disclosure Service Platform (全国互联网金融登记披露服务平台) indicates that the withdrawals were not driven by the fundamentals of the loans ("What is the key to the steady

Table 1
Summary statistics, loans.
The table reports summary statistics for loan applications (panel A) and funded loans (panel B) on Renrendai, over the period 2010–2017. One observation corresponds to a loan. All variables are defined in detail in Appendix A.

	N. obs.	Mean	St. dev.	P10	P50	P90
A. Loan applications						
Loan amount ('000 ¥)	955,405	64.54	80.34	5.00	50.00	124.50
Interest rate (%)	955,405	12.56	2.62	10.00	12.00	15.00
Maturity (months)	955,405	21.44	11.56	6	24	36
Financed (0/1)	955,405	0.39	0.49	0	0	1
B. Funded loans						
Loan amount ('000 ¥)	376,219	70.10	50.40	20.00	62.00	126.20
Interest rate (%)	376,219	11.27	1.40	9.60	10.80	13.20
Maturity (months)	376,219	29.96	9.46	18	36	36
Number of lenders	376,219	81.52	108.80	12	45	189
Open to 1st investment (min.)	376,219	1,372	3,229	3.18	221.31	4,103
1st to last investment (min.)	376,219	30.80	247.10	0.03	0.47	13.1
Default (0/1)	376,219	0.01	0.10	0	0	0

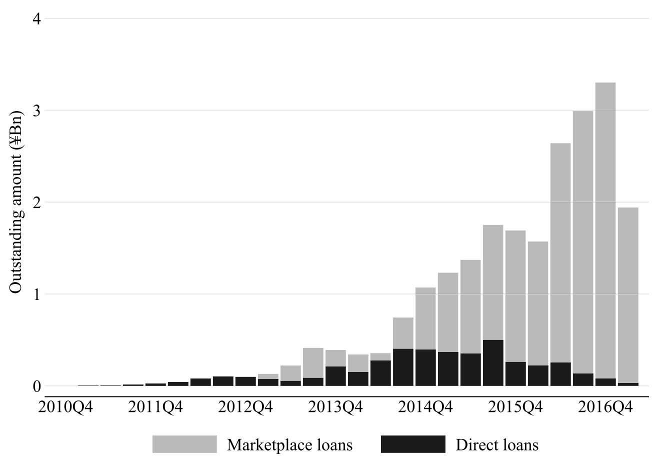

Fig. 1. Direct and marketplace loans at Renrendai, 2010Q4–2017Q1.
The figure plots the outstanding volumes of loans at Renrendai, for each calendar quarter over the period 2010–2017. The dark bars denote direct, or peer-to-peer, loans, and the lighter-shaded bars loans that are part of portfolio products, i.e., marketplace loans.

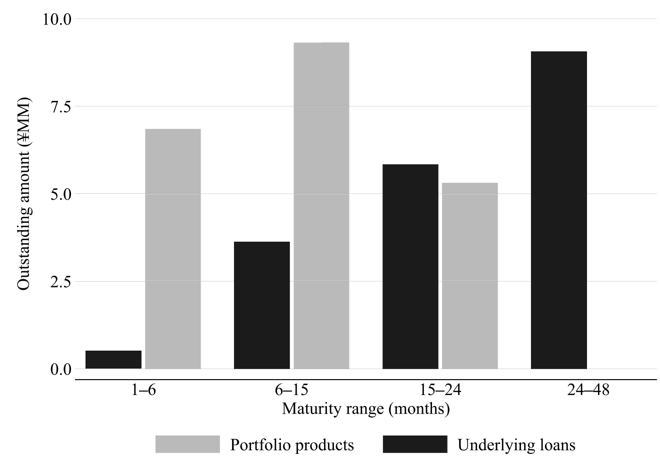

Fig. 2. Maturity mismatch on Renrendai's portfolio products.
The figure plots the outstanding amounts of portfolio products sold by Renrendai and their underlying loans by maturity bins. The light bars represent the total outstanding amounts of portfolio products. The dark bars represent the total amount of outstanding loans underlying the portfolio products.

2.3. Data; loan applications, funded loans, and portfolio products

Our data cover 955,405 loan applications and 376,219 funded loans, associated with 358,383 borrowers and 351,333 lenders on Renrendai. They report detailed information on loan applications, funded loans, portfolio products, borrower characteristics, and individual lender IDs. Table 1 presents descriptive statistics for loan applications and funded loans. Around 40% of loan applications ultimately obtain funding, and among those the average default rate is 1%. The median loan funded on the platform has size of about ¥62,000 ($9000) and maturity of 36 months; it pays a 10.8% annual interest rate, and is financed by 45 lenders. To contain dimensionality, we aggregate these data into categories based on loan size, maturity, interest rate, and borrower creditworthiness, defined in Appendix A.

Table 2 provides descriptive statistics for the portfolio products sold on Renrendai. The median portfolio product offers an 8.5% return, has a maturity of 6 months, a total size of ¥3 million, and a minimum investment amount of ¥1000. For each portfolio product, we also observe every investment that the platform makes on behalf of each lender and the exact time of the investment, as well as whether the lenders roll their investments over at maturity; just over 12% of portfolio investments are rolled over on average. When lenders liquidate their investment, we can measure the time until the portfolio share is sold on the secondary market, or resale time: on average, about half a day.[6]

The resale time of portfolio shares at maturity plays an important role in our analysis, as it captures the liquidity risk that lenders face when investing in a portfolio product. On average the secondary market for loans is liquid, but the resale time distribution has a thick right tail. Out of 2810 portfolio products in our data, around 9.5% have resale time in excess of one day. For these cases, the mean resale time is 4.2 days and the maximum is 88 days. Note that all lenders investing in the same portfolio face the same resale time, as the platform waits until all non-rolled over loans are sold on the secondary market before liquidating lenders.

development of Renrendai?", *Tencent*, 15 August 2019. "Renrendai Yang Yifu: Compliant operation is the most basic capability of online lending platforms", *China Finance*, 10 May 2019). This is confirmed by the low default rates of the loans issued by Renrendai right before 2020, which were 0.67% in 2018, 0.19% in 2019 and 0.10% in the first quarter of 2020 (source: Renrendai's annual reports).

[6] Table 2 reports resale time in units of days, which are immediately interpretable. In the regressions reported below in Tables 4 and 7, we express it as a fraction of one year for consistency with the other explanatory variables, which are in annual terms.

Table 2
Summary statistics, portfolio products.
The table reports summary statistics for portfolio products offered on Renrendai, over the period 2010–2017. One observation corresponds to a portfolio product. The number of observations is smaller for Rollover rate and amount, because portfolio products in the earlier years did not provide the rollover option, and for Resale time because around one third of portfolio products have not reached maturity by the end of our sample period, so that a resale time cannot be observed.

	N. obs.	Mean	St. dev.	P10	P50	P90
Size (million ¥)	3,973	5.07	6.78	0.20	3.00	10.00
Target return (%)	3,973	8.27	1.50	6.00	8.50	10.00
Maturity (months)	3,973	8.46	5.76	1	6	12
Loans per portfolio	3,971	8,767	7,982	1,475	6,908	17,916
Lenders per portfolio	3,973	286	263	62	216	603
Investment time (minutes)	3,973	1,120	1,597	14	712	2,832
Rollover rate (%)	3,383	12.34	13.57	0.00	9.20	32.67
Rollover amount ('000 ¥)	3,383	872	2,296	0.00	165	1,820
Resale time (days)	2,810	0.53	2.57	0.00	0.01	0.88

Table 3
Summary statistics, borrowers and lenders.
The table reports summary statistics for borrowers (panel A) and lenders (panel B) on Renrendai, over the period 2010–2017. One observation corresponds to one borrower in panel A, and in panel B respectively to one day for the first two variables, a day-lender for the third, and to one lender for the remaining four. All variables are defined in detail in Appendix A.

	N. obs.	Mean	St. dev.	P10	P50	P90
A. Borrowers						
Credit rating	746,735	4.71	2.48	2	7	7
Age	746,735	34.18	10.79	26	32	46
Homeowner (0/1)	740,082	0.37	0.48	0	0	1
Mortgage (0/1)	740,082	0.19	0.39	0	0	1
Male (0/1)	700,620	0.78	0.42	0	1	1
Monthly income ('000 ¥)	598,820	12.52	13.00	3.50	7.50	35.00
Tier 1 city (0/1)	568,755	0.13	0.34	0	0	1
B. Lenders						
Active lenders (%)	2,299	5.89	4.57	2.80	5.15	9.44
Tot. invest./day (mln. ¥)	2,299	17.80	26.53	0.02	4.31	57.15
Investment/day ('000 ¥)	17,551,212	2.33	15.50	0.05	0.25	3.75
Tot. investment ('000 ¥)	367,154	111.48	462.53	1.10	17.32	233.20
Active days	367,154	47.80	90.20	1	11	135
Portfolios invested	374,809	4.01	6.39	1	2	9
Loan categories invested	111,140	51.43	179,84	1	5	108

2.4. Borrowers and lenders; maturity mismatch and liquidity risk

Table 3 displays descriptive statistics for Renrendai's borrowers and lenders. The average borrower is 34 years old, male, and has a monthly gross income of ¥12,520 ($1880). Annual income per capita in China as of the end of our sample in 2017 is ¥25,974 ($3900; ¥2,165 per month), and in Beijing, the wealthiest part of the country, ¥57,230 ($8600; ¥4,769 per month; source: National Bureau of Statistics of China).

Fig. 2 describes the distribution of the maturities of portfolio products and their underlying loans. The most popular portfolio products have maturities under 12 months, and no portfolio has maturity beyond 24 months. Their underlying loans, on the other hand, have longer maturities, with the bulk of the distribution beyond 15 months. This evidence indicates the extent of maturity mismatch and the potential exposure to liquidity risk: portfolio products with maturity 3, 6, or 12 months comprise loans with maturity almost exclusively 24 or 36 months, and the weighted-average portfolio product maturity mismatch is about 22 months. This value is close to estimates of maturity mismatch for consumer credit at traditional banks reported in the literature (e.g., Drechsler et al., 2021, Table A.2). Only a small portion of the loans in the average portfolio product (0.14%) matures prior to the product's expiration; in those cases, the proceeds on those loans are reinvested by the platform.

The data, moreover, suggest that changes in investor population accompany the growth of Renrendai (and of debt crowdfunding in general). We observe a downward trend among investor portfolios in concentration (with the HHI going from 17% in 2010–2013 to 12% in 2014–2017) and default rates (from 2.4% in 2010–2013 to 0.5% in 2013–2017), driven especially by the Uplan portfolios. That is consistent with the arrival on the platform of investors who are more focused on limiting risk than on seeking yield. These new lenders are less likely to pick individual loans, but prefer to delegate their portfolio choices to Renrendai.

To capture those changes and reflect the increased investor heterogeneity, we focus on the percentage of active lenders on the platform on a given day. We define a lender as active if she is in the top 5% of the distribution of platform use, defined as the number of times she invested up to that date.[7] This variable reflects familiarity with the platform and/or laxer financial constraints: because Renrendai requires a minimum investment amount, more frequent investments indicate that the lender has greater financial resources, and should therefore be less liquidity risk-averse. We compute the daily share of active investors as the ratio of active investors to the total number of lenders investing on the platform on a given day. Descriptives for this variable are reported in Table 3.

3. Model

Our model features three players: borrowers, lenders, and a debt crowdfunding platform. Appendix Figure D.1 provides a graphical summary of the model.

[7] To control for the time trend in this measure, which might skew the frequency of active lenders towards the end of the sample period, we define the top 5% based on the platform use distribution within each calendar quarter. As an alternative, we replace the active lenders share by 1 minus the share of first-time platform users; the underlying assumption is that first-time users may be more risk averse. We find that it has a qualitatively similar relation to lender preferences as the active lenders share. These results are omitted for brevity but available upon request.

3.1. Borrowers

Borrowers post loan applications and, conditional on the loan being funded, make monthly repayments. We treat borrowers as passive agents, which keeps the model tractable and helps us highlight the key drivers in the counterfactuals, where we compare marketplace credit to the alternative lending paradigms, peer-to-peer and bank-like credit. This assumption is justified by three reasons. First, default rates are low (1% on average). This suggests that even if the platform shifts to a bank-like paradigm and attracts a different type of borrower, those borrowers would be at best only marginally safer than under marketplace credit. Second, nearly 80% of loan applications and over 95% of funded loans are made by individuals active on Renrendai only once. These individuals are unlikely to be so familiar with the platform as to condition their decisions on expected lender demand or on the platform's business model. Moreover, as they typically appear only once, it also unlikely that the platform will face an insolvency–illiquidity spiral, where borrowers struggle to roll over their loans due to lenders' concerns about rising default rates. Third, borrower characteristics do not exhibit much variation over time, particularly around 2014, when marketplace loan portfolios became the main funding channel.[8] This attenuates the possibility that, even though the typical borrower interacts with the platform only once, different *types* of borrowers may approach the platform in response to a change in the lending model.

3.2. Lenders

We model the lenders' investment decisions using a discrete choice framework, where the lenders choose among loans and portfolio products based on their characteristics. Conditional on investing in a portfolio product, lenders can decide to roll their investment over at maturity, or cash it out facing the liquidity risk. Every day t a set of lenders $i = 1, \ldots, I_t$ can invest on the platform. Each lender can choose between investing in direct loans, identified by superscript D, or in a portfolio product, identified by superscript P; if she invests in a portfolio product, at maturity she also faces the choice between rolling over and liquidating.

In principle, lenders can choose among a large set of direct loans, either newly posted or trading in the secondary market. Those loans are differentiated by observable characteristics such as yield, maturity, amount, and a number of borrower attributes. To keep the lenders' choice set computationally tractable, we group direct loans in discrete categories $c = 1, \ldots, C_t^D$, which include loans that are homogeneous in terms of observable characteristics and are available to direct lenders on day t. Each day a lender can invest in at most one portfolio product or one direct loan category; she can, however, still form a portfolio of direct loans by investing in different categories across multiple days.[9] A direct lender chooses to invest in a given loan category based on the utility she derives from its characteristics. The indirect utility of lender i investing in loan category c on day t is:

$$U_{ict}^D = \underbrace{\begin{matrix} \gamma_{it}^r \ln\left(r_{ct}\right) + \gamma_{it}^m \ln\left(m_{ct}\right) + \gamma_{it}^a \ln\left(a_{ct}\right) \\ +\gamma_{it}^{\mathcal{L}} \mathcal{L}_{ct}^D + \gamma_{it}^z z_{ct} + \zeta_{ct} \end{matrix}}_{\delta_{ict}^D} + \varepsilon_{ict}, \tag{1}$$

where r_{ct} denotes the loan category's yield, m_{ct} its maturity, a_{ct} its amount, and z_{ct} are other characteristics of the loan category observable to the lender (all variables in Panel A of Table 3, plus *time to first investment* and *time from first to last investment* from Table 1). $\mathcal{L}_{ct}^D$ denotes loan category c's liquidity, defined as the time it takes for category c's loans to be resold on the secondary market at maturity, or resale time. We group log-yield, log-maturity, log-amount, resale time, and z_{ct} in a vector x_{ct}; ζ_{ct} are normally distributed demand shocks at the loan category–day level unobserved by the econometrician, and ε_{ict} is a Type 1 Extreme Value shock; letting γ_{it} denote the vector of coefficients, we define $\delta_{ict}^D = \gamma_{it}' x_{ct} + \zeta_{ct}$. We do not explicitly model lenders' sensitivity to a single variable capturing borrower's default risk, but rather assume that the borrower and loan characteristics included in Eq. (1) are used by lenders to predict risk, with credit rating likely the best predictor.

To allow for heterogeneity in lender preferences, in Eq. (1) the coefficients can vary across lenders i and over time t. This approach captures the stylized facts described in Section 2, specifically any shift in the composition of the lender population towards those with a lower tolerance for liquidity risk. It also serves as an additional proxy for regarding lenders as patient or impatient as in Diamond and Dybvig (1983), with investors with lower tolerance being more impatient. As a proxy for liquidity risk-tolerance we use a measure of the lenders' activity on the platform.

Each lender can also invest in a portfolio product $k = 1, \ldots, K_t$ among those available on a given day t. As remarked, we observe lenders funding both portfolio products and direct loans simultaneously only very rarely; we thus treat these two options as mutually exclusive.[10] The indirect utility of lender i choosing portfolio product k on day t is:

$$U_{ikt}^P = \underbrace{\begin{matrix} \alpha_{it}^{\mathcal{R}} \ln\left(\mathcal{R}_{kt}\right) + \alpha_{it}^{\mathcal{M}} \ln\left(\mathcal{M}_{kt}\right) + \alpha_{it}^{\mathcal{A}} \ln\left(\mathcal{A}_{kt}\right) \\ +\alpha_{it}^{\mathcal{L}} \mathcal{L}_{kt} + \alpha_{it}^{\mathcal{Z}} \mathcal{Z}_{kt} + \xi_{kt} \end{matrix}}_{\delta_{ikt}^P} + \eta_{ikt}, \tag{2}$$

where $\mathcal{R}_{kt}$ denotes the target return of portfolio product k, offered on the platform on day t, $\mathcal{M}_{kt}$ its maturity, and $\mathcal{A}_{kt}$ its target size; $\mathcal{Z}_{kt}$ are other portfolio characteristics observable to the lender that we describe in detail in Section 5. $\mathcal{L}_{kt}$ denotes the portfolio product's liquidity, defined as the time it takes for its underlying loans to be resold on the secondary market at maturity, and it embodies the cost of early liquidation as in Diamond and Dybvig (1983). We assume the lenders and the platform have perfect foresight about portfolio liquidity. As in Eq. (1), the model's coefficients are allowed to vary across lenders and over time and we group log-target return, log-maturity, log-investment amount, liquidity, and $\mathcal{Z}_{kt}$ in a vector of characteristics $\mathcal{X}_{kt}$. ξ_{kt} are normally distributed shocks to demand at the portfolio product–day level unobserved by the econometrician, and η_{ikt} is a Type 1 Extreme Value shock; α_{it} denotes the vector of coefficients, and $\delta_{ikt}^P = \alpha_{it}' \mathcal{X}_{kt} + \xi_{kt}$.

When the portfolio product reaches maturity, lenders decide whether to roll it over (at the same conditions as they originally invested) or to liquidate their investment. The indirect utility from rolling over is:

$$U_{ikt}^{Roll} = \tau^{\mathcal{R}} \mathcal{R}_{kt} + \tau^{\mathcal{M}} \mathcal{M}_{kt} + \tau^{\mathcal{A}} \mathcal{A}_{kt} + \tau^{\mathcal{Z}} \mathcal{Z}_{kt} + \tau^{\mathcal{L}} \mathcal{L}_{kt} + \nu_{ikt}, \tag{3}$$

where ν_{jkt} is a normally distributed shock.

Finally, lenders have the outside option of investing outside the platform or not investing at all. Ideally, we would like to capture what part of the population of potential lenders (market size) does not invest on the platform on a given day. To proxy for that, we assume that the day with the largest amount invested in a given calendar quarter

[8] For example, borrowers' monthly income is on average ¥8,600 (USD 1290) up to 2014 and ¥8,800 (USD 1320) after 2014, borrowers' age is about 34 years on average both before and after 2014, and 43.37% (47.51%) of the borrowers have a college (or higher) degree up to (after) 2014.

[9] This assumption is justified by the data, as conditional on investing, the median number of loan categories or portfolio products in which a lender invests on a given day is 1. It is also motivated by the potential search costs that lenders face when searching through a large number of loans on the platform. If a category has no loan applications on a given day t, then that category will not be part of the lenders' choice set on day t. Notice however that throughout the sample period there are always multiple loan categories and multiple portfolio products available for lenders on each day.

[10] Out of 13,398,102 lender–date observations, we observe lenders holding both a portfolio product and direct loans in 155,604 cases (1.16%).

corresponds to the potential market size in that quarter and define that as $\mathcal{T}_t$; on a given day t, the market share of the outside option is $\mathcal{T}_t$ minus the lenders' total invested amount. We normalize the indirect utility from choosing the outside option to zero.

The indirect utility from Eq. (1) determines the probability that lender i invests in loan category c on day t:

$$\mathcal{S}^D_{ict}(x_{ct}, \mathcal{X}_{kt} \mid \gamma_{it}, \alpha_{it}) = \frac{\exp(\delta^D_{ict})}{1 + \sum_{c\in C^D_t} \exp(\delta^D_{ict}) + \sum_{k\in K_t} \exp(\delta^P_{ikt})}. \tag{4}$$

Similarly, the indirect utility from Eq. (2) determines the probability that lender i invests in portfolio product k at time t, $\mathcal{S}^P_{ikt}$, whose expression is analogous to Eq. (4); and the indirect utility from Eq. (3) determines the probability that she rolls over her investment in portfolio k as opposed to cashing out, $\mathcal{S}^{Roll}_{ikt}$. The fact that the denominator of Eq. (4) includes the direct-lending terms (superscript D) as well as the marketplace-lending terms (superscript P) indicates that our model allows lenders to consider a direct substitution between direct lending loan categories and portfolio products.

3.3. Platform

The platform maximizes profits by choosing three variables: (i) the target return, (ii) the maturity mismatch of each portfolio product and (iii) the resale time of the underlying loans.

We treat the platform's portfolio choice as an asset demand model based on loan characteristics. Each day t, the platform decides on the features of each portfolio product $k = 1, \ldots, K_t$ that it offers and selects the underlying loans accordingly. We assume that the loan characteristics x_{ct}, as defined in Section 3. 3.2, also identify the loan categories $c = 1, \ldots, C^P_t$ that the platform considers when creating portfolio products. However, the set of loan categories available to the platform for its portfolios, C^P_t, can differ from those available to direct lenders, C^D_t, because the platform invests only in loans to AA or A borrowers. This restriction mechanically eliminates all categories with borrowers rated below A, and it reflects how the platform internalizes investors' aversion towards default risk when choosing portfolio products.

The platform receives a total renminbi amount $\mathcal{T}_t \times \sum_{k\in K_t} \mathcal{S}^P_{kt}$ on day t to invest in portfolio products. That amount is allocated across portfolios based on their market shares $\mathcal{S}^P_{kt}$, which aggregate the individual lender demands $\mathcal{S}^P_{ikt}$ defined in the previous section. For a given portfolio product k, the total investment amount $\mathcal{T}_t\mathcal{S}^P_{kt}$ is entirely allocated across loan categories, with w_{kct} being the weight of loan category c in portfolio k.

To determine the weights w_{kct}, we assume that the platform's demand for loan categories depends on their characteristics in a way similar to the discrete-choice framework discussed in the previous section. This allows us to match observed portfolio weights to recover the platform's "preferences" for those characteristics. The weight w_{kct} of loan category c in portfolio product k offered on the platform on day t is:

$$w_{kct} = \frac{\exp(\delta_{kct})}{\sum_{g\in C^P_t} \exp(\delta_{kgt})}, \tag{5}$$

where:

$$\delta_{kct} = \beta^r_{kt} r_{ct} + \beta^m_{kt} m_{ct} + \beta^a a_{ct} + \beta^z z_{ct} + \beta^d d_{ct} + v_{kct}, \tag{6}$$

and v_{kct} are normally distributed demand shocks at the portfolio–loan category–day level unobserved by the econometrician. This functional form and approach are similar in spirit to Koijen and Yogo (2019).[11] Eq. (6) describes the platform's preferences for loan characteristics associated with a given portfolio product. We let the platform have heterogeneous preferences, varying across portfolio products k and days t, for the most relevant loan characteristics: yield and maturity. β^r_{kt} indicates the platform's preference for loans with higher yields, and β^m_{kt} the platform's preference for loans with longer maturities in portfolio k. A larger β^m_{kt} will generate portfolios containing a larger proportion of loans with longer maturities. As a result, β^m_{kt} drives the maturity mismatch in a given portfolio product, and thus determines the exposure to liquidity risk.[12] For these reasons, we focus our analysis, and the platform's optimization problem discussed below, on these two parameters.

We assume that the platform predicts the average default rate d_{ct} for each loan category c on each day t based on past defaults in that category up to day t. We operationalize this by including defaults rates in Eq. (6), whereas we do not include them in Eq. (1). The assumption is justified by the fact that the platform has access to the complete performance history of all loans, whereas individual lenders only have access to partial information on past performance and face higher costs in collecting and processing these data. Additionally, the borrower and loan characteristics observed by lenders represent the information they use to assess a loan's default risk. The platform's preference for using the average default rate of a loan category reflects how it internalizes investors' aversion to default risk in its portfolio choices.

In our counterfactual analysis of Section 6, we combine the estimates of the lender demand model with the structure of the platform's portfolio choice to simulate the welfare effects of alternative scenarios. That requires modeling how the platform adjusts its target return, maturity mismatch, and resale time to maximize profits. On each portfolio product, the platform earns a profit Π_{kt} given by:

$$\Pi_{kt} = \mathcal{T}_t\mathcal{S}^P_{kt}\left[\sum_{c\in C^P_t} w_{kct}\left(r_{ct} - C_{1ct}\right) m_{ct} - \mathcal{R}_{kt}\mathcal{M}_{kt} - \frac{C_{2kt}}{1 + \ln\left(1 + \mathcal{L}^P_{kt}\right)} - C_{3kt}\right] \tag{7}$$

where $\mathcal{T}_t\mathcal{S}^P_{kt}$ is the renminbi amount invested in portfolio product k. The terms in square brackets denote the percentage return that the platform earns on that investment net of its costs. Revenues on portfolio k are measured by $\sum_c w_{kct} r_{ct} m_{ct}$, i.e., the platform earns an annualized return r_{ct} on loan category c, over a duration of m_{ct} years.[13] From that amount, we subtract (i) a marginal cost C_{1ct}, capturing the cost of locating and monitoring loans in a given category c; (ii) the target return $\mathcal{R}_{kt}$ paid out to lenders for a duration of $\mathcal{M}_{kt}$ years; (iii) a cost C_{2kt}, capturing the cost of increasing the liquidity $\mathcal{L}_{kt}$ of loans in portfolio product k; and (iv) an administrative cost C_{3kt} net of borrowers' fees, which characterizes portfolio k and does not vary across loan categories.

The profit function includes a separate term for the cost of generating liquidity, $\frac{C_{2kt}}{1+\ln(1+\mathcal{L}_{kt})}$. The functional form is motivated by three considerations. First, $\mathcal{L}_{kt}$ in the denominator ensures that an increase in resale time reduces the cost of providing liquidity. $\mathcal{L}_{kt}$ should be part of the cost, for otherwise the platform would always want to set $\mathcal{L}_{kt}$ to zero to maximize market shares. Second, given the skewed distribution of $\mathcal{L}_{kt}$, the logarithm helps capture the diminishing marginal reduction in liquidity cost as $\mathcal{L}_{kt}$ increases. Third, when $\mathcal{L}_{kt}$ is small the denominator approaches 1, which justifies adopting the form $1 + \ln\left(1 + \mathcal{L}_{kt}\right)$.

The platform can provide liquidity by buying a loan and including it in a new portfolio product, or indirectly by increasing its marketing efforts. Incorporating a given loan in a new portfolio product more

[11] Koijen and Yogo (2019) formally derive the multinomial logit demand as the solution to a mean–variance portfolio choice problem. We abstract from such a formal derivation and rely on the flexibility of (6) to capture the relationship between loan characteristics and the portfolio products weights.

[12] We take the set of available portfolio product maturities as given, as it remains fixed throughout our data.

[13] As in Benetton (2021), in Eq. (7) we abstract from discounting given the short duration of the underlying loans (1 month to 4 years in our data, 2 to 5 years in Benetton, 2021).

quickly can be difficult, however, because there is only a limited amount of funds that investors put into the platform to finance new portfolios; as a result, there is an opportunity cost of liquidating a given loan faster relative to another one. The term in C_{2kt} in Eq. (7) captures this cost.

The platform chooses portfolio product characteristics and composition so as to maximize its overall profit. Operationally, the platform optimally determines the target return $\mathcal{R}_{kt}$, preference for underlying loan maturity β^m_{kt}, and resale time $\mathcal{L}_{kt}$ for each portfolio product.[14] The platform solves:

$$\max_{\{\mathcal{R}_{kt},\beta^m_{kt},\mathcal{L}^P_{kt}\}} \Pi_t = \sum_k \Pi_{kt}. \tag{8}$$

The solution to problem (8) determines the composition of each portfolio product.

3.4. Equilibrium

Every day t, lenders can invest in C^D_t loan categories, available both in the primary and secondary markets for direct loans, and in K_t loan portfolios. The equilibrium is characterized by the conditions defining the lenders' utility maximization problem, together with the platform's portfolio allocation and profit maximization problems.

In the primary market, the supply of loans is exogenously given as we treat borrowers a passive agents. The demand for loans is defined by the direct lenders' market share Eq. (4) and the loan portfolio product weights given by Eq. (5). The lenders and the platform take loan promised interest rates, amounts, and maturities as given, and decide whether to fund the application.

In the secondary market, the supply of loans is given by the fraction of loan portfolios that are not rolled over, which in turn is determined by Eq. (11). An institutional feature of Renrendai is that loans are resold at their face value. Because the resale price cannot be adjusted, lenders who do not roll over their portfolios may have to hold their loans until a buyer is available; the resale time variable $\mathcal{L}_{kt}$ captures this feature of the secondary market for each portfolio k at its maturity.

The demand for loans is defined, as in the primary market, by the direct lenders' market share Eq. (4) and the platform's portfolio weights (5). For each portfolio product k on day t, demand equals supply in equilibrium. The supply of portfolio products is determined by the platform maximization problem (8), and the demand by their market shares $\mathcal{S}^P_{kt}$.

We define the equilibrium as a set of target returns $\mathcal{R}_{kt}$, resale times $\mathcal{L}^P_{kt}$, and maturity preferences β^m_{kt} such that (i) the platform maximizes the profit function in Eq. (8); (ii) for each k and c, the portfolio weight of loan category c in portfolio product k satisfies Eq. (5); (iii) for each k, the portfolio product market share satisfies Eq. (10); (iv) the market share of loans in the secondary market satisfies Eq. (11); and (v) the market share of direct loans satisfies Eq. (4).

4. Estimation

We estimate the model outlined above to recover lender preferences for loans and portfolio products, the determinants of the investment rollover decision, and the platform's preferences for loan characteristics.

Our approach builds on the logit demand model for differentiated products by Berry (1994), which estimates preference parameters from market shares. We define market shares based on the probability that a given lender chooses a particular loan category, as specified in Eq. (4), and similarly for portfolio products. To account for heterogeneity in lender preferences, we use activity on Renrendai as an index of lender sophistication and liquidity risk tolerance. Intuitively, only lenders with greater financial capacity and higher liquidity risk tolerance can frequently meet the minimum investment cost. To aggregate this measure across all lenders in Eq. (4), we focus on the percentage of active lenders (those in the top 5% of the active investing distribution in a given calendar quarter) among all investors on the platform on a given day t, denoted by $\mathcal{E}_t$. This represents the probability that a lender is active. We can express the coefficients in Eqs. (1) and (4) as $\gamma_t = \bar{\gamma} + \varsigma\mathcal{E}_t$, dropping the subscript j, where $\bar{\gamma}$ captures the preferences of the most inactive lenders, and ς measures the deviation from this baseline driven by a higher probability of lender activity. This approach allows us to capture the average preferences of lenders, ranging from active to inactive, and thus control for the potential non-stationarity of the distribution of lender preferences.

Next, denote by $\mathcal{S}^D_{ct}$ the market share of loan category c on day t and by $\mathcal{S}_{0t}$ the market share of the lenders' "outside option" of not investing on Renrendai. The natural logarithm of the ratio between $\mathcal{S}^D_{ct}$ and $\mathcal{S}_{0t}$ is linear in the preference parameters, so that we can estimate:

$$\begin{aligned}\ln(\mathcal{S}^D_{ct}) - \ln(\mathcal{S}_{0t}) = {} & \gamma^r_t \ln(r_{ct}) + \gamma^m_t \ln(m_{ct}) + \gamma^a_t \ln(a_{ct}) \\ & + \gamma^{\mathcal{L}}_t \mathcal{L}_{ct} + \gamma^z_t z_{ct} + \mu_D + \mu_t + \zeta_{ct},\end{aligned} \tag{9}$$

where the main explanatory variables are loan return r, maturity m, amount a, and liquidity $\mathcal{L}$, and z collects other loan attributes; μ_D is an indicator for the direct loans investment channel, μ_t are day fixed effects, and ζ_{ct} are shocks.

A similar expression obtains for the lenders' investment in portfolio products:

$$\begin{aligned}\ln(\mathcal{S}^P_{kt}) - \ln(\mathcal{S}_{0t}) = {} & \alpha^{\mathcal{R}}_t \ln(\mathcal{R}_{kt}) + \alpha^{\mathcal{M}}_t \ln(\mathcal{M}_{kt}) + \alpha^{\mathcal{A}}_t \ln(\mathcal{A}_{kt}) \\ & + \alpha^{\mathcal{L}}_t \mathcal{L}_{kt} + \alpha^{\mathcal{Z}}_t \mathcal{Z}_{kt} + \mu_P + \mu_t + \xi_{kt},\end{aligned} \tag{10}$$

where $\mathcal{R}$ denotes the portfolio's target return, $\mathcal{M}$ its maturity, $\mathcal{A}$ the target size of the portfolio, $\mathcal{L}_{kt}$ liquidity risk (resale time on the secondary market), and $\mathcal{Z}$ collects other observable attributes of the portfolio; μ_P is an indicator for the portfolio investment channel, μ_t are day fixed effects, and ξ_{kt} are shocks. We write Eqs. (9) and (10) separately for expositional convenience, but they are actually part of a single demand system that combines lender choices to invest in direct loans and portfolio products, and allows for direct substitutability between the two channels. The two equations are hence jointly estimated as part of one regression model.[15]

We estimate the determinants of the rollover decision using ordinary least squares. In this case, the dependent variable is the proportion of investment portfolio product k that is rolled over by investors, which we denote with $\mathcal{S}^{Roll}_{kt}$:

$$\mathcal{S}^{Roll}_{kt} = \tau^{\mathcal{R}}\mathcal{R}_{kt} + \tau^{\mathcal{M}}\mathcal{M}_{kt} + \tau^{\mathcal{A}}\mathcal{A}_{kt} + \tau^{\mathcal{Z}}\mathcal{Z}_{kt} + \tau^{\mathcal{L}}\mathcal{L}_{kt} + \psi_t + \nu_{kt}, \tag{11}$$

where ψ_t denote day fixed effects and ν_{kt} are shocks.

Finally, we estimate the platform's demand for loans in a similar fashion as for Eqs. (9) and (10), but with the difference that the

[14] We solve the platform's optimization problem as a function of the maturity preference parameter β^m_{kt} rather than portfolio product maturity for tractability. There are only a handful of portfolio maturity options available on the platform (3, 6, 12, 18, and 24 months), whereas focusing on β^m_{kt} allows us to work with a continuous variable. Moreover, given portfolio maturity, β^m_{kt} determines the extent of maturity mismatch, so that optimizing with respect to β^m_{kt} is isomorphic to optimizing with respect to portfolio maturity.

[15] Alternative approaches could be a mixed logit model (Train, 2009) or the random coefficients logit demand model of Berry et al. (1995). We do not choose the mixed logit approach to contain dimensionality and because it would be difficult to identify individual lenders' choice of an outside option. We also do not implement the Berry et al. (1995) approach as it would increase computational complexity, since it does not have a closed form solution for the market shares, and because our strategy already captures similar heterogeneity in lender preferences. The Berry et al. (1995) approach would identify the mean and standard deviation of the lender preferences' distribution, while our approach delivers estimates of baseline preference parameters and deviations from the baseline.

platform does not have an outside option, as it needs to invest the whole amount raised from lenders across loan categories. Hence, to be able to identify the preference parameters we normalize all δ_{kct} with respect to one of the alternatives within portfolio k issued on day t. This leads to the following specification:

$$\begin{aligned}\ln(w_{kct}) - \ln(w_{k0t}) = \; & \beta^r_{kt}\left(r_{ct} - r_{0t}\right) + \beta^m_{kt}\left(m_{ct} - m_{0t}\right) \\ & + \beta^a\left(a_{ct} - a_{0t}\right) + \beta^z\left(z_{ct} - z_{0t}\right) \\ & + \beta^d\left(d_{ct} - d_{0t}\right) + \phi_t + v_{kct},\end{aligned} \tag{12}$$

where w_{k0t} represents the share invested in the loan category with respect to which all other categories are normalized, r_{0t}, m_{0t}, a_{0t}, z_{0t}, d_{0t} are its corresponding attributes, ϕ_t are day fixed effects, and v_{kct} are shocks.

Identifying the lenders' preference parameters and the platform's demand for loans relies on the assumption that the demand shocks ζ_{ct}, ξ_{kt}, and v_{kt} are uncorrelated with interest rates, loan amounts, and maturities, conditional on the control variables z ($\mathcal{Z}$), the channel (direct loan/portfolio), and day fixed effects. This assumption could be violated if there are omitted variables, where the demand shocks capture loan or portfolio qualities known only to lenders and correlated with interest rates, loan amounts, or maturities. We address this concern by leveraging the institutional features of our setting: our detailed data allows us to observe the same information available to lenders. Thus, we can control for every product or loan attribute that investors see when accessing the platform, significantly reducing the risk of omitted variables.

A second potential challenge to identification is simultaneity. This could be an issue if the borrowers are able to observe a loan category–day specific demand shock faced by the lenders (Eqs. (9)–(10)) or the platform (Eq. (12)) and strategically adjust their loan applications. Such a degree of sophistication, however, is unrealistic: around 80% of loan applications are submitted by borrowers using the platform for the first time, and Renrendai provides them with no information on the lenders' or the platform's past choices.

Although the platform's institutional setting helps mitigate potential identification concerns, we also use instrumental variables for portfolio returns and loan interest rates in the lenders' demand model to ensure the robustness of our findings. We employ the heterogeneous pass-through of monetary policy, measured by the Shibor index, across portfolio products and loan categories, following Villas-Boas (2007) and Egan et al. (2017). The idea is that when Shibor rises, the cost of credit for borrowers at traditional intermediaries increases, which subsequently raises the interest rates posted by borrowers on the platform and the returns offered by the platform on its portfolios. This pass-through varies across portfolio products and loan categories due to differences in maturity structures and the diverse maturity preferences of borrowers and lenders. By including day fixed effects, we control for the direct effect of Shibor changes on lenders' demand, ensuring Shibor impacts demand only through changes in portfolio returns and loan interest rates.

5. Results

In this section we present the estimates of the models from Section 4. Table 4 describes the lenders' demand for direct loans and portfolio products, both for the OLS (columns 1 and 3) and IV (columns 2 and 4) estimates. As we find that almost all OLS and IV coefficients are not statistically different from each other, we focus on the OLS estimates in this section and in the discussion of the counterfactuals in Section 6 (we provide counterfactual results using the IV estimates in the Appendix).

Lender utility is an increasing function of yields for direct loans (columns 1 and 2) as well as for portfolio products (column 3 and 4), even more so when there are more active lenders on Renrendai. Moreover, the sensitivity to direct loans returns is higher than for portfolio product returns. As a gauge for that, we look at the estimates of the elasticity of demand with respect to loan and portfolio returns reported in the first two rows of Table 5, which assess the economic significance of the results of Table 4 considering different percentiles in the distribution of the daily proportion of active lenders. A 10% (83 bps) higher target return increases the demand for a given loan category by 12.1% on average; in comparison, a 10% higher return raises portfolio product demand on average by only 6.5%. We find that lenders prefer larger loans and portfolios, and such preference does not depend on their level of activity on the platform.

The sensitivity of lenders' utility to the resale time of loans underlying portfolio products is higher compared to loans invested through direct lending; however, it declines when we focus on active investors. The corresponding demand elasticity is reported in Table 5; on average, a 10% increase in resale time $\mathcal{L}$ (about 1.3 h) reduces portfolio product demand by 0.030%. However, that same 10% increase in resale time reduces demand from less active lenders (10th percentile) by 0.073%, while it reduces demand from more active lenders (90th percentile) by less than 0.001%. In contrast, as shown in Table 4, the coefficients on resale time for direct lenders are always smaller and never statistically significant.[16]

The estimates of the platform's demand for loan categories are summarized in Table 6 and Appendix Figure D.2. Table 6 shows that on average the platform favors loans offering lower returns and longer maturities. We interpret these results as suggesting that the platform uses both the interest rates and maturities set by the borrowers to alleviate adverse selection problems. Riskier borrowers offer high interest rates and shorter maturities as they may struggle to obtain funding otherwise. In the spirit of Stiglitz and Weiss (1981), by forming portfolios with loans offering lower interest rates and longer maturities, the platform obtains lower returns on the average loan but extends credit to a pool of safer borrowers.[17] This interpretation is corroborated by the results in Table 6, which show that the platform avoids loan categories with higher default rates.[18] We also find that, ceteris paribus, the platform prefers primary market loans to loans available on the secondary market. This makes intuitive sense because primary market loans are more profitable to the platform, as the borrowers pay a fee when they obtain a loan, but not when the loan is resold.

Finally, Table 7 describes the lenders' rollover decision. Rollover probability for a portfolio product is increasing in its return and size, and decreasing in maturity. The estimates of Table 7 suggest that portfolio product characteristics have little impact on the fraction of the

[16] The differences in the Table 4 coefficients between direct lending and portfolio products can be due to characteristics such as return or maturity having a different impact on indirect utilities depending on whether they are associated to direct loans or portfolio products ("treatment"), or to different investor types selecting into direct lending or portfolio product investment ("selection"). Under the "treatment" interpretation, for a given level of the % of active lenders all investors are ex-ante similar, in line with the assumptions of Diamond and Dybvig (1983); under the "selection" interpretation, investors are ex-ante similar within each investment channel (direct loans or portfolio products).

[17] Hertzberg et al. (2018) find that on LendingClub, a U.S. marketplace credit platform, riskier borrowers tend to choose longer maturities and pay higher interest rates to be insured against unfavorable refinancing conditions. On Renrendai, however, borrowers have more flexibility, and interest rates are only required to be within a broad range, so maturity is not used as a screening tool. Interestingly, that contrasts with the behavior of direct lenders, who, as we discussed, favor higher returns. Our interpretation of these results for the borrowers is that the latter do not learn that by posting lower interest rates they may increase their chances of being funded. This argument is backed by our institutional setting: Over 95% of funded loans are granted to borrowers using the platform for the first time.

[18] Note that we use the realized default rates in each loan category up to time t. In other words, we assume that the platform can predict the average defaults in each category using the information it holds about the past records on loan performance.

Table 4
Lenders' demand for portfolio products and direct loans.
The table reports the estimates of Eqs. (9) and (10), estimated as one regression model, encompassing both. One observation is one loan category or portfolio product on one day. Portfolio product controls include indicators for two special portfolios launched in the early days of the platform called "Beginner Uplan" and "Bonus Uplan". Loan category controls include the borrower characteristics in Table 3 and Appendix A. Channel fixed effects include indicators for Direct lending (reported), Uplan (reported), and Salary Plan (excluded category). The first and third columns report the OLS estimates, the second and fourth columns the corresponding IV estimates. The standard errors, reported in parentheses, are clustered around interactions of days, channel, and promotional portfolio products, for a total of 3697 clusters.

	Direct loan		Portfolio product	
	OLS	IV	OLS	IV
Log Return (r_{ct}, $\mathcal{R}_{kt}$)	0.58	0.34	0.24	0.11
	(0.13)	(0.12)	(0.15)	(0.18)
Log Return (r_{ct}, $\mathcal{R}_{kt}$) ×Active lenders %	11.36	10.37	8.72	10.99
	(1.90)	(1.81)	(1.62)	(2.05)
Log Maturity (m_{ct}, $\mathcal{M}_{kt}$)	0.23	0.27	0.28	0.24
	(0.02)	(0.02)	(0.04)	(0.04)
Log Maturity (m_{ct}, $\mathcal{M}_{kt}$) ×Active lenders %	−1.02	−1.28	0.06	0.44
	(0.26)	(0.29)	(0.30)	(0.39)
Log Amount (a_{ct}, $\mathcal{A}_{kt}$)	0.57	0.55	0.63	0.55
	(0.01)	(0.01)	(0.04)	(0.04)
Log Amount (a_{ct}, $\mathcal{A}_{kt}$) ×Active lenders %	0.59	0.69	−2.30	−0.55
	(0.15)	(0.16)	(0.46)	(0.50)
Resale Time ($\mathcal{L}_{ct}$, $\mathcal{L}_{kt}$)	−1.49	−0.68	−8.73	−11.04
	(3.40)	(3.38)	(2.72)	(3.29)
Resale Time ($\mathcal{L}_{ct}$, $\mathcal{L}_{kt}$) ×Active lenders %	34.49	16.41	108.19	148.08
	(48.48)	(48.14)	(44.94)	(54.98)
Channel f.e.	2.22	1.42	2.25	2.23
	(0.40)	(0.45)	(0.04)	(0.05)
Portfolio product controls	Yes			
Loan category controls	Yes			
Day f.e.	Yes			
N. obs.	75,810			
Adj. R^2 (OLS estimates)	0.708			
Kleibergen–Paap F Statistic (IV estimates)	71.81			

Table 5
Lenders' demand elasticities with respect to return and liquidity risk.
The table reports the distribution of the coefficients $\gamma_t^{\mathcal{R}} = \bar{\gamma}^{\mathcal{R}} + \varsigma^{\mathcal{R}}\mathcal{E}_t$, $\gamma_t^r = \bar{\gamma}^r + \varsigma^r\mathcal{E}_t$, $\alpha_t^{\mathcal{L}} = \bar{\alpha}^{\mathcal{L}} + \varsigma^{\mathcal{L}}\mathcal{E}_t$ depending on the distribution of $\mathcal{E}_t$, the daily proportion of active lenders on the platform.

	N. Obs.	Mean	St. Dev.	P10	Median	P90
Direct Loans Return	1,131	1.2101	0.2158	1.0053	1.1626	1.4764
Portfolio Return	718	0.6455	0.2041	0.4517	0.6230	0.8776
Portfolio Resale Time	718	−0.0030	0.0106	−0.0073	−0.0007	−0.0000

portfolio that is rolled over. The coefficients on target return and resale time are insignificantly different from zero at conventional levels, and the coefficients on maturity and portfolio size, although significantly different from zero, imply small economic effects.[19]

These estimates allow us to compute the relative market shares of each portfolio product k and each loan category c and back out the structural parameters in the platform's profit function C_{1c}, C_{2k}, and C_{3k} and to perform a further check against the data providing some indications about the validity of our framework. The cost C_{2k} should be inversely related to the expected liquidity available on the platform when portfolio k reaches maturity. We thus relate the values of C_{2k} implied by the model to the renminbi inflow of new investments on the platform on the days when each portfolio matures. Appendix Figure D.3 illustrates this check. Consistent with our model, we find a negative and statistically significant relation between C_{2k} and new investment flow: where new investment is more modest, providing liquidity is more costly for the platform. We overlay a linear regression on top of the scatterplot of C_{2k}–log-investment inflow pairs; the slope of the line is

Table 6
Platform's demand for direct loans.
The table reports the estimates of Eq. (12). One observation is one day–loan category. Standard errors in parentheses are clustered at the day level. Loan Category Controls include the variables listed in the Borrowers panel of Table 3.

	Mean	Standard deviation
Return (r_{ct})	−0.31	1.49
Maturity (m_{ct})	0.10	0.08
Amount (a_{ct})	0.69	
	(0.09)	
Default rate borrowers (d_{ct})	−0.56	
	(0.12)	
Secondary market loan	−0.31	
	(0.17)	
Loan category controls	Yes	
Day f.e.	Yes	
N. obs.	95,028	
Adj. R^2	0.630	

[19] In the estimates of Table 7, maturity is expressed in years. The coefficient estimate of −0.01 implies that a one-year shorter maturity is associated with a 1 percentage point larger share of the portfolio that is rolled over. Given that the longest portfolio product maturity in our data is three years, the effect is very modest. Similarly, a one-standard deviation (¥6.78 million) increase in portfolio size is associated with a 6 percentage points higher rollover rate.

Table 7
Rollover rate of portfolio products.
The table reports the estimates of Eq. (11). One observation is one day–portfolio product. Standard errors in parentheses are clustered at the day level. Portfolio product controls include indicators for two special kinds of Uplan launched in the early days of the platform called "Beginner Uplan" and "Bonus Uplan", and indicators for other types of promotional plans.

Target return ($\mathcal{R}_{kt}$)	0.69
	(0.87)
Maturity ($\mathcal{M}_{kt}$)	−0.01
	(0.00)
Amount ($\mathcal{A}_{kt}$)	0.01
	(0.00)
Resale time ($\mathcal{L}_{kt}$)	−0.32
	(0.54)
Portfolio product controls	Yes
Day f.e.	Yes
N. obs.	2,928
Adj. R^2	0.515

–0.0012 (standard error: 0.0006), which implies that a one-standard deviation higher log-inflow is associated with a 19.5% lower in C_{2k}.

6. Counterfactuals

6.1. Design of the counterfactual scenarios

We simulate scenarios changing three key features of the platform. First, we eliminate portfolio products, so that lenders can only choose between peer-to-peer credit and the outside option. That allows us to quantify the welfare value of intermediation by the platform. Second, we simulate a "bank-like" scenario where the platform sells loan portfolio products as under the marketplace model, but bears liquidity risk like a traditional bank. That allows us to study the impact of the maturity mismatch between portfolio products and their underlying loans. We simulate several versions of this counterfactual, corresponding to different levels of the platform's cost of generating liquidity. Third, we replicate the bank-like counterfactual, changing the composition of the lender population by reducing the incidence of active lenders. That allows us to understand which lenders benefit the most from marketplace credit and which from bank-like credit.

In the bank-like counterfactuals, we modify our model to attribute liquidity risk-bearing to the platform. That involves two changes. First, the resale time variable $\mathcal{L}$ is removed from the lenders' indirect utility and rollover decision equations. Second, the profit on a given portfolio product k is now written as:

$$\Pi_{kt} = \mathcal{T}_t S^P_{kt} \Bigg\{ \underbrace{\sum_{c \in m \le \mathcal{M}} w_{kct}\left(r_{ct} - C_{1kct}\right) m_{ct}}_{\text{Not exposed to liquidity risk}} + \underbrace{\sum_{c \in m > \mathcal{M}} \left[w_{kct}\left(r_{ct} - C_{1kct}\right) m_{ct} - w_{kct} r_{ct} \left(1 - S^{Roll}_{kt}\right) \frac{m_{ct}}{\mathcal{M}_{kt}} \ell_{kct} \mathcal{L}_{kt} \right]}_{\text{Exposed to liquidity risk}} - \mathcal{R}_{kt}\mathcal{M}_{kt} - \frac{C_{2kt}}{1 + \ln\left(1 + \mathcal{L}_{kt}\right)} - C_{3kt} \Bigg\} \quad (13)$$

The profit function can be divided into two revenue and two cost components, respectively the first two and last two terms in the braces on the right hand side of Eq. (13). The first revenue term denotes platform's net returns on loans with maturity $m \le \mathcal{M}$, i.e. shorter than or equal to the portfolio product's maturity $\mathcal{M}$. In this case there is no mismatch between portfolio and loan maturities and no liquidity risk. The return obtained by the platform is a weighted average of the annual return paid by borrowers r_{ct} times the maturity (expressed in years) of each loan category m_{ct}, where the weights are given by the portfolio weights w_{kct} defined in Eq. (5).

The second revenue term denotes loans with maturity $m > \mathcal{M}$, i.e., longer than the portfolio maturity $\mathcal{M}$. In this case the platform is exposed to liquidity risk, and will have to refinance the underlying loans when the portfolio product reaches its maturity. A loan can be refinanced in two ways. First, the original lender may roll her portfolio investment over; that happens with probability S^{Roll}_{kt} from Eq. (11). In that case, the lender's investment is prolonged, and the platform keeps receiving the borrower's interest payments as revenues. Second, the lender may not roll her investment over; that happens with probability $1 - S^{Roll}_{kt}$. In that case, the underlying loans are moved to the secondary market, where they can be bought by a direct lender or they can be taken up to become part of a new marketplace loan portfolio. Either way, a resale time elapses, which comes with a loss of revenue for the platform, captured by the term $w_{kct} r_{ct} \left(1 - S^{Roll}_{kt}\right) \frac{m_{ct}}{\mathcal{M}_{kt}} \ell_{kct} \mathcal{L}_{kt}$. In that term, $\frac{m_{ct}}{\mathcal{M}_{kt}}$ reflects the maturity mismatch between portfolio k and the underlying loan category c.[20] The larger the maturity mismatch between the portfolio and the underlying loans, the larger the loss of revenues, which the platform incurs $\frac{m_{ct}}{\mathcal{M}_{kt}}$ times. $\mathcal{L}_{kt}$ is the portfolio's resale time, corresponding to the maximum resale time among all loan categories included in portfolio k. ℓ_{kct} is a number between 0 and 1, corresponding to the ratio between the resale time of loan category c and resale time of the loan category that takes the longest to be resold (equivalent to $\mathcal{L}_{kt}$).[21]

Note that the platform knows the aggregate distribution of the liquidity shocks indicated by S^{Roll}_{kt} and tilts portfolio weights towards more vs less maturity mismatch via the maturity preference parameter β^m_{kt} to maximize profits. This further aligns our model with the Diamond and Dybvig (1983) framework, as the platform applies the law of large numbers with the intention of ensuring sufficient liquidity for investors wishing to liquidate.

6.2. Comparing the three paradigms

In Table 8 we document how the outcomes predicted by our model change between the baseline case (i.e., marketplace lending, base cost of liquidity, and base proportion of active lenders) and the alternative scenarios (direct lending and bank-like, both with base cost of liquidity and proportion of active lenders).[22]

In the first place, restricting credit to direct (peer-to-peer) lending induces a welfare loss. In Table 8 we show that it is associated with a 73% drop in credit provision and a 31% lower lender surplus in comparison to the baseline case.[23] That highlights the substantial benefits of platform intermediation through portfolio products, and provides a rationale for the transition to the marketplace model. The drop in

[20] For simplicity, our model assumes that the platform's refinancing cost is equal to the weighted average of the interest rates of the loans in the portfolio product. We also conducted robustness checks allowing for different external financing costs, both lower and higher than this average, but the main conclusions of our counterfactuals remain unchanged.

[21] If the platform assumed default risk in addition to liquidity risk under the bank-like paradigm, the effects would be ambiguous. While credit supply might expand to include lower-quality borrowers, the platform would have stronger incentives to screen them, potentially improving the creditworthiness of marginal borrowers. Importantly, Renrendai's portfolio products are limited to highly rated loans (AA or A), suggesting that even with an expanded credit supply, the platform prioritizes high-quality loans. Moreover, given that our data is from a single platform and that measures of Renrendai's default risk, such as CDS spreads, are not available during our sample period, we cannot directly analyze platform default risk as in Egan et al. (2017).

[22] In Appendix Tables D.1 and D.2 we report the same counterfactual results, but based on the IV estimates of Table 4 instead of the OLS ones. Results are qualitatively and quantitatively very similar.

Table 8
Base liquidity cost: marketplace, bank-like, and peer-to-peer credit.
Changes are always relative to the baseline case of marketplace lending with base liquidity cost and base percentage of active lenders. The levels of lenders' surplus and platform's profit for the baseline case are normalized to zero.

Outcome	Marketplace	Bank-like	Peer-to-peer
Average return (%)	8.15	8.79	
Average maturity mismatch (months)	20.94	17.07	
Average resale time (days)	0.42	38.95	
Amount lent (bn ¥)	19.64	19.67	5.32
Amount lent Uplan (bn ¥)	16.55	16.64	0.00
Average change lenders' surplus (%)	0.00	0.34	−31.44
Average change platform profit (%)	0.00	−1.68	

lender surplus and credit provision can be due to three, non-mutually exclusive factors: (a) a search cost advantage, if the platform is able to locate loans in which to invest faster than peer-to-peer lenders, (b) an information advantage, if the platform is better able to screen and/or monitor borrowers, or (c) the bigger choice set under the marketplace model for the lenders, as portfolio products can have a shorter maturity than the underlying loans.

The median time until the first investment is 245 min for loans funded by peer-to-peer investors and 307 min for loans that become part of portfolio products, suggesting that search costs are not economically very different between peer-to-peer investors and the platform. To determine the impact of the platform's information, we simulate an additional counterfactual, in which we remove the default rate d_{ct} from the determinants of the platform's portfolio weights in Eq. (6), so that the peer-to-peer lenders and the platform have access to identical information. The results of this counterfactual are virtually identical to those reported in Table 8. This suggests that the platform's information is also not the main driver of the difference in lender surplus and credit provision between the marketplace and peer-to-peer models. This is perhaps not surprising: the platform can only invest in loans to borrowers with credit rating A or AA, which are less subject to adverse selection problems. The main driver appears to be the fact that maturity mismatch allows the platform to offer a greater assortment of portfolios to the lenders, who are not constrained to invest in loans matching their investment horizon.[24]

Table 8 also shows that under base liquidity and base active lenders bank-like credit has very similar outcomes relative to marketplace credit. Credit provision levels are almost identical and lender surplus increases by 0.34% in relative terms. The platform's profits are only 1.68% lower than under the marketplace model, and resale time in the secondary market is significantly longer. This can be explained by the platform having a lower cost of refinancing compared to individual investors. For example, the platform can access external financing more cheaply to refinance loans that are not rolled over. Note that in this counterfactual, the bank-like platform bears liquidity risk but not default risk; in this sense, what we attempt to identify is the value of an intermediary specifically taking liquidity risk and we do not capture default risk.

6.3. Increasing liquidity costs and inactive lenders

The differences between the marketplace and bank-like paradigms become more visible in Table 9, where we examine the impact of liquidity risk and lender population composition on outcomes generated under the two paradigms. In all the scenarios simulated in Table 9, we assume that the platform's cost C_{2kt} of generating liquidity increases by 10% relative to the baseline scenarios of Table 8. We also consider alternative compositions of the lender population, captured by the proportion of active lenders $\mathcal{E}_t$. In columns (1)–(2), we set that to the same level as in the baseline of Table 8; in columns (3)–(4), we reduce it by 30%, so that the average lender is expected to be less active, and hence less sensitive to yield and more liquidity risk-averse.

We begin by examining the impact of increased liquidity risk while keeping the proportion of less active (risk-averse) investors constant. Relative to the baseline scenario in Table 8 (baseline level of liquidity cost), we observe notable differences between the marketplace and bank-like paradigms. Under the bank-like paradigm, returns offered to portfolio investors increase, while they decrease under the marketplace paradigm. Returns decrease under marketplace credit because the platform passes-through the higher liquidity costs to lenders. Under bank-like credit instead, the increase in returns is driven by two factors. First, some portfolios become unprofitable due to the higher liquidity costs, and the platform offers near-zero returns on those to minimize losses. Second, to make up for the loss of investment in those unprofitable portfolios, the platform increases returns on the portfolios that are still profitable, leading to an average increase in returns. Conversely, the liquidity gap (measured by resale time) narrows as resale time increases under marketplace credit, since in the marketplace model the platform does not bear the liquidity risk. The gap in maturity mismatch between the two paradigms remains close to Table 8. The gap in the amount lent expands, with credit provision decreasing in the marketplace paradigm and rising in the bank-like paradigm. Similarly, lender surplus declines under marketplace credit, because of the lower returns and the higher resale time, but it grows under bank-like credit, due to the higher returns. Platform profits, however, decrease more substantially under bank-like credit due to the platform incurring higher liquidity generation costs. In sum, with a higher cost of generating liquidity, the marketplace model yields higher profits for the platform compared to the bank-like model. The opposite is true for lenders and borrowers.

The welfare comparison changes, however, in columns (3)–(4), where we reduce the proportion of active lenders skewing the lender population towards having greater liquidity risk aversion and a lower sensitivity to yields on average. Under that scenario, the bank-like paradigm is welfare-improving across all three dimensions: we observe greater credit provision, lender surplus, and platform profits than under the marketplace paradigm. This happens because less active lenders increase the amount they invest in the portfolio products as the platform insures them against liquidity risk. Higher lending volumes more than compensate the cost of bearing the liquidity risk, thus increasing the platform's profits. This results provides a rationale for the existence of marketplace credit alongside traditional banks. When liquidity risk is limited and online credit platforms attract more sophisticated, less liquidity risk-averse investors, the marketplace model can be optimal. In contrast, when liquidity risk is higher and/or when investors

[23] Under direct credit the platform makes no profits other than through fees, which we omit as they are minimal on the lender side (¥2 for a ¥10,000 withdrawal). Borrower fees are also small for the high-rated borrowers targeted by the platform's portfolio products, and we leave them outside our analysis as our focus is on the lenders. The average daily profit for the platform under the marketplace paradigm is around ¥1.7 bn, which would be lost under the peer-to-peer scenario.

[24] The "maturity mismatch" outcome reports the simple average of portfolio products' maturity mismatch.

Table 9
High liquidity cost: marketplace and bank-like, base and low active lenders.
Changes are always relative to the baseline case of marketplace lending with base liquidity cost and base percentage of active lenders. The levels of lenders' surplus and platform's profit for the baseline case are normalized to zero.

Active lenders share:	Base		Low	
Outcome	Marketplace	Bank-like	Marketplace	Bank-like
Average return (%)	8.08	9.17	6.47	8.61
Average maturity mismatch (months)	20.94	17.14	20.94	16.97
Average resale time (days)	12.85	39.55	73.57	40.68
Amount lent (bn ¥)	18.69	19.93	21.10	22.48
Amount lent Uplan (bn ¥)	15.48	16.93	17.16	18.76
Average change lenders' surplus (%)	−3.56	2.55	18.42	21.73
Average change platform profit (%)	−18.27	−24.20	−11.27	−8.02

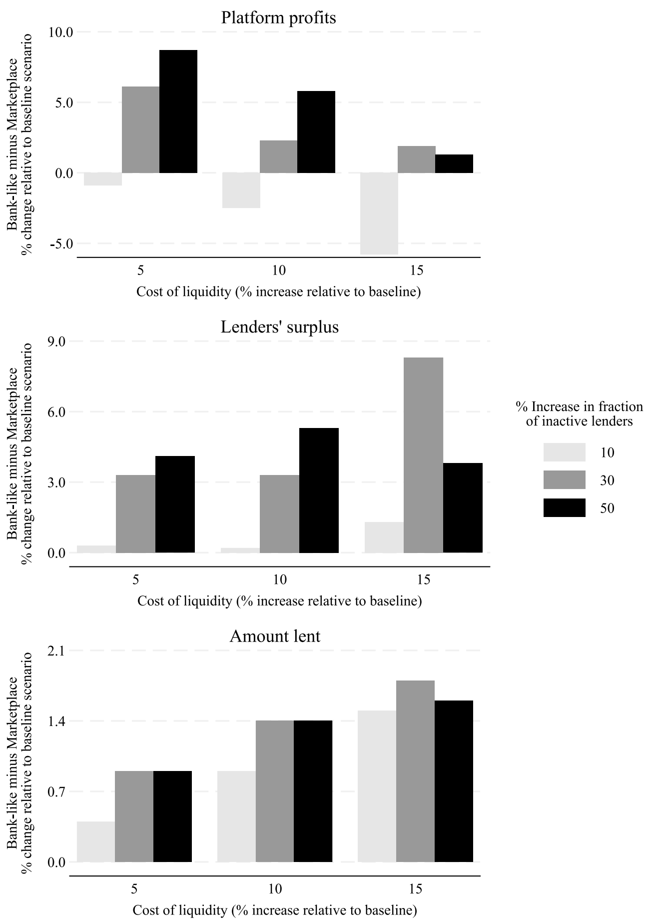

Fig. 3. Sensitivity analysis.
The figure summarizes the results of counterfactuals simulated under different values of the increase in the cost of generating liquidity C_2 (5%, 10%, and 15%) and the increase in the portion of less active lenders (10%, 30%, 50%) relative to the baseline that assumes the marketplace paradigm and average cost of generating liquidity. The graphs plot the difference in platform profits, lender surplus, and amount lent under the bank-like paradigm minus the corresponding quantity under the marketplace paradigm; positive values imply that the bank-like paradigm dominates, negative values that the marketplace paradigm dominates.

are more liquidity risk-averse, traditional intermediation dominates (corresponding to the bank-like paradigm in our counterfactual).[25]

6.4. Sensitivity analysis

Fig. 3 compares the bank-like and marketplace paradigms across varying liquidity costs and fractions of inactive lenders. Typically, platform profits are higher in the bank-like paradigm, except when fewer lenders are inactive. The bank-like paradigm becomes less dominant for the platform when liquidity costs rise. This happens because, although the platform generally attracts more lenders under the bank-like scenario, it still incurs liquidity costs through a higher value of C_{2k}. As liquidity costs rise, the bank-like model incurs an additional expense to raise external funds (as shown in Eq. (13)). When the increase in C_{2k} is large enough, these additional costs outweigh the extra revenue generated by attracting more lenders in the bank-like scenario.

The bank-like paradigm benefits lenders more than the marketplace paradigm because it protects them from liquidity risk. As a result, lenders receive a higher surplus and are more willing to invest, leading to more borrowers being financed. This effect is particularly strong when liquidity costs are low or moderate, and when the proportion of inactive, risk-averse lenders is not too high. When liquidity costs are high and many lenders are inactive, the bank-like model is still preferred, but its advantage becomes less pronounced. This is because the platform faces high external financing costs, forcing it to offer lower returns. With a higher proportion of inactive lenders, more are willing to accept lower returns in exchange for avoiding liquidity risk. While this protection benefits inactive lenders, it does not fully offset the losses experienced by active lenders, who prioritize higher returns over risk insurance.

Taken together, these results are consistent with a narrative in which, in the early days of online debt crowdfunding, the sector mainly attracts risk-tolerant lenders, who seek higher returns and have higher welfare under the peer-to-peer and marketplace models. As the clientele of lenders grows, it comes to encompass more risk-averse investors, who are more sensitive to liquidity risk and have higher welfare under the bank-like model. Moreover, our findings are in line with anecdotal evidence about the most developed platforms such as LendingClub, Funding Circle, Zopa, or RateSetter, which have shut down peer-to-peer credit, while offering securitized (marketplace) loan portfolios to a more risk-tolerant institutional investor clientele as well as, more recently, traditional banking products to more risk-averse retail investors.[26]

7. Conclusion

We develop and estimate an equilibrium model of online debt crowdfunding as a laboratory to study the value of financial intermediation. We exploit the fact that under different online lending paradigms the crowdfunding platform plays different roles: under the peer-to-peer paradigm it merely provides a trading venue to lenders and borrowers;

[25] The bank-like model can be fragile under conditions of extreme illiquidity. Appendix Table D.3 reports an additional counterfactual, where the rollover probability is set to zero. As a result, platform profits, lender surplus, and amount lent drop substantially, suggesting that the bank-like model can be suboptimal under such a scenario.

[26] An important caveat to this interpretation is that, during our sample period, Renrendai's lenders were essentially all retail and comprised, to our knowledge, no institutional investors.

under the marketplace credit paradigm it sells to investors loan portfolios that exhibit maturity mismatch, but bears no liquidity risk; and more recently under the bank-like paradigm if offers to retail investors products that resemble traditional bank deposits. Our empirical setting attenuates the potential confounding effects of regulation, since online credit was very lightly regulated in China during our sample period, and of the complexity of the business of traditional intermediaries, since online lending platforms focus exclusively on intermediating credit in our sample.

We estimate our model using the universe of loans and loan applications on Renrendai, a leading Chinese marketplace credit platform. Our approach recovers lender preferences from observed investment choices, and allows us to simulate counterfactuals to contrast marketplace credit to the peer-to-peer lending and bank-like paradigms.

We show a transition away from peer-to-peer lending and towards marketplace credit, and we document and quantify the exposure to liquidity risk that it creates. Moreover, we provide evidence of lender heterogeneity: less active investors on the platform are less focused on yields and more averse to liquidity risk. Our counterfactual analysis points to two main results. First, moving from the peer-to-peer to the marketplace model raises lender surplus, platform profits, and credit provision, suggesting a Pareto improvement. Second, the marketplace and bank-like models have similar welfare performance when the cost of generating liquidity and lender liquidity-risk aversion are low, but the bank-like model is welfare-increasing when the cost of generating liquidity and lender liquidity-risk aversion are high. Note that, whereas the bank-like paradigm can offer advantages in terms of liquidity provision, our results show that it can be more exposed to rollover risk under stress scenarios. The history of banking crises shows that banks' commitment to providing liquidity can be costly in bad times.

Overall, our findings highlight the importance of liquidity risk on debt crowdfunding platforms, in particular, and financial intermediaries more in general. They also contribute to the ongoing regulatory debate, especially relevant as online credit intermediaries increasingly compete with traditional players.

CRediT authorship contribution statement

Fabio Braggion: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alberto Manconi:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nicola Pavanini:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Haikun Zhu:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflict of interests that relate to the research described in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2025.104113.

Data availability

The Value of Financial Intermediation: Evidence from Online Debt Crowdfunding (FINEC-D-23-00120) (Reference data) (Mendeley Data)

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