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Abstract

We study the welfare effects of the transition of online debt crowdfunding from the older "peer-to-peer" model to the "marketplace" model, where the crowdfunding platform sells diversified loan portfolios to investor. We develop an equilibrium model of debt crowdfunding capturing platform design (peer-to-peer or marketplace) and lender preferences over loan and portfolio product characteristics, and we estimate it on a novel database on credit at a large online platform based in China. Moving from the peer-to-peer to the marketplace model raises lender surplus, platform profits, and credit provision. At the same time, reducing lender exposure to liquidity risk can be beneficial. A counterfactual scenario where the platform resembles a bank by bearing liquidity risk has similar welfare properties as the marketplace model when liquidity is high, but results in larger lender surplus and credit provision, and only moderately lower platform profits, when liquidity is low.

JEL classification: D14, D61, G21, G51, L21
Keywords: Marketplace credit, Chinese financial system, Structural estimation

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1 Introduction

Online debt crowdfunding is an increasingly important consumer credit and investment channel. Averaging yearly growth rates well above 100%, the segment has reached \$284 bn in outstanding loans in 2016 (Rau 2019). Debt crowdfunding has moved from an older "peer-to-peer" model, where lenders pick the individual loans they fund, to a "marketplace" model, where the crowdfunding platform sells loan portfolio products to lenders (Balyuk and Davydenko 2019, Vallée and Zeng 2019). That has brought platforms closer to traditional banks, in that portfolio products are shorter-term liabilities invested in longer-term loans. Unlike bank depositors, however, marketplace lenders bear liquidity risk: they can only cash out their investment once the underlying loans are sold on the platform's secondary market.

We study the effects of the new business model on lenders, platforms, and credit provision. We develop an equilibrium model of debt crowdfunding capturing platform design (peer-to-peer, marketplace) and lender preferences over loan and portfolio product characteristics, and we estimate it on a novel database on credit at a large online platform. We find that moving from the peer-to-peer to the marketplace model raises lender surplus, platform profits, and credit provision. At the same time, reducing lender exposure to liquidity risk can be beneficial. A counterfactual scenario where the platform resembles a bank by bearing liquidity risk has similar welfare effects as the marketplace model when liquidity is high, but yields larger lender surplus and credit provision, and only moderately lower platform profits, when liquidity is low.

Our analysis is motivated by the observation that a welfare comparison between marketplace, peer-to-peer, and traditional bank credit is not obvious. Marketplace lenders are exposed to liquidity risk; but compared to peer-to-peer lenders, they face lower search, diversification, and adverse selection costs; and compared to bank depositors they earn higher returns. In turn, lowering costs and increasing returns for lenders, as well as shielding the platform from liquidity risk, incentivize credit provision, benefiting borrowers. Quantifying these tradeoffs is crucial to inform regulation and to address growing concerns about liquidity risk on online credit platforms (BIS 2017).[1] Thus,

[1]These concerns have also been voiced in the press, see e.g. "Peer-to-peer lending needs tighter regulation," *Financial Times* 11 September 2018; "China curbs 'Wild West' P2P loan sector," *Financial Times* 5 April 2017, and

we must assess the costs and benefits of alternative platform designs on the data.

Measuring those costs and benefits, however, confronts us with three empirical challenges. First, it requires counterfactuals. The ideal experiment compares outcomes for otherwise identical platforms under the marketplace model, the peer-to-peer model, and a bank-like version of the marketplace model where the platform bears liquidity risk. But little peer-to-peer credit exists any longer, and no platform adopted the bank-like model as yet—and if one were to introduce it, its launch would not be randomly assigned.[2] Second, the welfare impact of platform design depends on how lender preferences trade off expected return and liquidity risk. But those preferences are intrinsically unobservable; and they are evolving, as marketplace credit reaches a larger, more heterogeneous investor pool. Third, liquidity risk exposure depends on the misalignment between lender, platform, and borrower horizons, and micro data are necessary to draw the link between a given lender's investment and the loans that the platform makes to borrowers.

We address these challenges with a structural estimation approach and with novel data. First, we build a model of online credit following the industrial organization literature on demand estimation for differentiated products (Berry 1994, Berry, Levinsohn and Pakes 1995). The model nests the marketplace, peer-to-peer, and bank-like platform designs, allowing us to simulate counterfactual scenarios and compare their welfare effects. Second, the model recovers lender preferences from observed investment choices, providing a measure of surplus and a way to account for lender heterogeneity in our counterfactuals. Third, we base our analysis on a hand-collected micro database covering the universe of loans and loan applications on Renrendai (人人贷), a leading Chinese debt crowdfunding platform. We observe the composition of portfolio products, and we can compare their maturity to that of the underlying loans to quantify liquidity risk exposure.

Our main findings are as follows. First, consistent with practitioner accounts and with the findings of Balyuk and Davydenko (2019), we observe a transition to marketplace credit: in 2010, when Renrendai was launched, 100% of lending was peer-to-peer; by the end of our sample in

"Funding Circle seeks to ease fears over withdrawal delays," *Financial Times* 11 October 2019.

[2]As a first-ever case, Zopa was granted a full U.K. banking license in December 2018 and has planned the introduction of fixed-term savings accounts ("P2P Lender Zopa Granted Full UK Banking License," *Financial Times* 4 December 2018).

early 2017, over 98% was marketplace. Our data indicate that this trend may have given rise to non-trivial liquidity risk: whereas most of Renrendai's portfolio products have maturities of 3, 6, or 12 months, the underlying loans typically mature in 36 months. Moreover, lender investments have become more diversified and less exposed to defaults, especially so for portfolio products purchased on the platform. That suggests a change in the platform's clientele, towards investors more averse to risk and less focused on yield.

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. Lenders prefer higher returns, especially for peer-to-peer loans, and portfolio products with lower liquidity risk, measured in terms of resale time on the secondary market. Moreover, the lenders' 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 and first-time users. We interpret this as evidence that lenders with more appetite for yield might benefit from the marketplace model, while others, more concerned about liquidity, might be better off under the bank-like model. We also find that Renrendai prefers longer-maturity, low-yield loans for portfolio products. That is consistent with an attempt to reduce adverse selection by avoiding the riskier borrowers, in line with Kawai, Onishi and Uetake (2016); but at the same time, it may exacerbate the maturity mismatch with the portfolio products, which typically have short maturity.

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 the expected returns on the portfolio products and the mismatch between portfolio duration and the maturity of the underlying loans. The marketplace model appears welfare-improving relative to the peer-to-peer model, raising credit provision and lender surplus by over 60%. We also find that, with a baseline level of liquidity (time to loan resale around half a day), bank-like credit results in identical loan volumes and lender surplus as marketplace credit, and a minimal drop in platform profits (0.2%).

That comparison is very different, however, under a "stress test" scenario where we raise the time to loan resale to one month.[3] Under that scenario, the marketplace model exhibits a larger decline relative to the bank-like model in credit provision (8% vs 1%) and lender surplus (34% vs 0.5%), but a smaller drop in platform profits (9% vs 12%). In other words, when liquidity is low the marketplace model is preferable from the platform's point of view, but worse for lenders and borrowers. The potential conflict between the interests of the platform, lenders, and borrowers might reflect the current reach of online debt crowdfunding and the features of the lender population. When, in a final counterfactual, we alter the lenders' composition to have weaker utility from yield and stronger disutility from liquidity risk on average, we find that the bank-like model is a Pareto improvement, raising platform profits too.

Our paper makes three main contributions. First, it provides new results on the design of online debt crowdfunding platforms. The literature has looked at adverse selection costs (Vallée and Zeng 2019) and pricing mechanisms (Franks, Serrano-Velarde and Sussman 2018) in online lending. We take a different, complementary angle. Building on the evidence of the shift to marketplace, or reintermediation (Balyuk and Davydenko 2019), we focus on liquidity risk and on measuring the welfare value of alternative platform designs. In that respect we also relate to the literature comparing online and traditional credit intermediaries (Buchak, Matvos, Piskorski and Seru 2018, de Roure, Pelizzon and Thakor 2018), as well as to the industrial organization literature on online marketplaces reviewed by Einav, Farronato and Levin (2016). Our results help rationalize the evolution of platform design from peer-to-peer to marketplace, and provide insight into its potential future development in light of the comparison with the bank-like model.

Second, our paper contributes to the literature on structural estimation in financial intermediation (Egan, Hortaçsu and Matvos 2017, Crawford, Pavanini and Schivardi 2018), online credit (Kawai et al. 2016, Xin 2018, Rahim 2018, Tang 2020), and online marketplaces in general (Diner-

[3] Although much longer than the baseline scenario, that is well within the range experienced by lenders on Renrendai (the maximum time to resale we observe is 88 days). It is also significantly less than the four months resale time observed on Funding Circle, the largest U.K. debt crowdfunding platform, in 2019 ("Funding Circle seeks to ease fears over withdrawal delays," *Financial Times*, 11 October 2019).

stein, Einav, Levin and Sundaresan 2018, Einav, Farronato, Levin and Sundaresan 2018, Fréchette, Lizzeri and Salz 2019, Farronato and Fradkin 2018). To the best of our knowledge, we are the first to develop a structural model of debt crowdfunding that explicitly incorporates peer-to-peer, marketplace, and bank-like credit. We provide a tractable framework to analyze the behavior of online credit platforms, which could be employed in further applications.

Third, and more broadly, our paper contributes to the literature on the value of financial intermediation. Intermediaries such as banks play a central role in the economy, facilitating the provision of credit for longer-term projects via maturity transformation (Diamond and Dybvig 1983), and bearing the fixed costs of information collection (Diamond 1984). These arguments are not controversial, but the literature provides little indication of the dollar value of intermediation. We take a first step in that direction, by contrasting "new" and "old" models of financial intermediation: peer-to-peer credit (where the platform bears neither maturity transformation nor information collection costs), marketplace credit (only information collection), and bank-like credit (both information collection and maturity transformation). Even if only in the context of online credit, our analysis is able to quantify the welfare benefits of the traditional functions of financial intermediation.

The rest of the paper is organized as follows. Section 2 describes the institutional development of online debt crowdfunding and our data, and provides preliminary descriptive evidence. Section 3 presents our structural framework modeling the choices of the lenders and the platform, and Section 4 outlines the estimation strategy. Section 5 discusses the results. Section 6 presents the counterfactuals. Section 7 concludes.

2 Institutional background, data, and descriptive evidence

A Development of the business model of online debt crowdfunding

Online debt crowdfunding initially emerged in the U.K. where Zopa, the first platform, was launched in 2005; it later spread to the U.S. and other larger economies. Crowdfunding reached China in 2007, with the launch of Paipaidai (拍拍贷), and has accounted for about 7.5% of total consumer credit over the period 2014–2019. Despite the introduction of regulatory restrictions following several scandals in 2016, many online credit platforms are still active in China—344 as of 2019. Lending online is popular among Chinese investors: the number of active lenders grew from 0.9 million in 2014 to almost 4.5 million in 2017.[4]

We base our analysis on a novel, hand-collected database covering the universe of loan applications and credit outcomes on a leading debt crowdfunding platform, Renrendai (人人贷). According to 01caijing (零壹财经), Renrendai is the fifth largest player in the sector in China, with a 5% market share. Between its launch in 2010 and the end of our sample period in February 2017, it has had a cumulative turnover of ¥25 billion ($3.7 billion) and has registered over 1 million active users between borrower and lender accounts.

Renrendai provides a good illustration of the salient features of online debt crowdfunding and the recent developments of its business model. Users can be borrowers or lenders. When submitting a loan application, a prospective borrower specifies the amount she seeks, and proposes an interest rate and time to maturity.[5] Renrendai pre-screens loan applications, assigning a credit score to borrowers.[6] Following this step, loan applications become visible to prospective lenders.

Lenders 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. Direct lenders can fund new loans or purchase outstanding loans on Renrendai's secondary market. Marketplace lenders can choose from a menu

[4]Source: Wang Dai Zhi Jia (网贷之家).

[5]The loan amount is restricted by borrowing ceilings set by the Renrendai, which depend on the borrower's credit score; the largest loan size obtainable on Renrendai is ¥1,000,000. The annual interest rate has to be in the range between 7% and 24%. The maturity options available to borrowers are 3, 6, 9, 12, 15, 18, 24, and 36 months. The prospective borrower is required to submit a number of verifiable personal information items used by the platform to determine her credit score. These include a copy of an identity document, a phone number, and her personal credit report from the Credit Reference Center of the People's Bank of China (中国人民银行征信中心). If the borrower is employed in a given company or organization, she also needs to submit a copy of her employment contract; if self-employed, a business certificate and a copy of the most recent transactions on her bank account.

[6]China does not have a credit registry, nor an established consumer credit score comparable to the U.S. FICO score. The credit score used on Renrendai is based on the information available to the platform. Throughout most of our sample period, Renrendai sets aside part of its revenues in a reserve pool, intended to compensate investors who suffered a default on the least risky loan categories. As of 2016Q3, the reserve pool had a size of ¥344,749,952, corresponding to 3.16% of the value of outstanding credit-certified loans. In 2016, reserve pools of this sort were abolished by the regulatory reform "Interim Measures for the Administration of the Business Activities of Online Lending Information Intermediary Institutions," (网络借贷信息中介机构业务活动管理暂行办法) issued mainly by China's banking regulatory commission, among a long list of organizations.

of portfolios known as Uplan (U计划). Renrendai offers every day a fresh set of Uplan portfolios, differentiated by target annual return (ranging between 6% and 11%), maturity (between 3 and 24 months), and minimum investment amount (¥1,000 or ¥10,000). At maturity, Uplan lenders can roll their investment over or cash out. If they cash out, the platform sells the underlying loans on the secondary market, and does not bear the liquidity risk: the lenders do not receive a payment until the corresponding loans have been sold.[7] 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.[8]

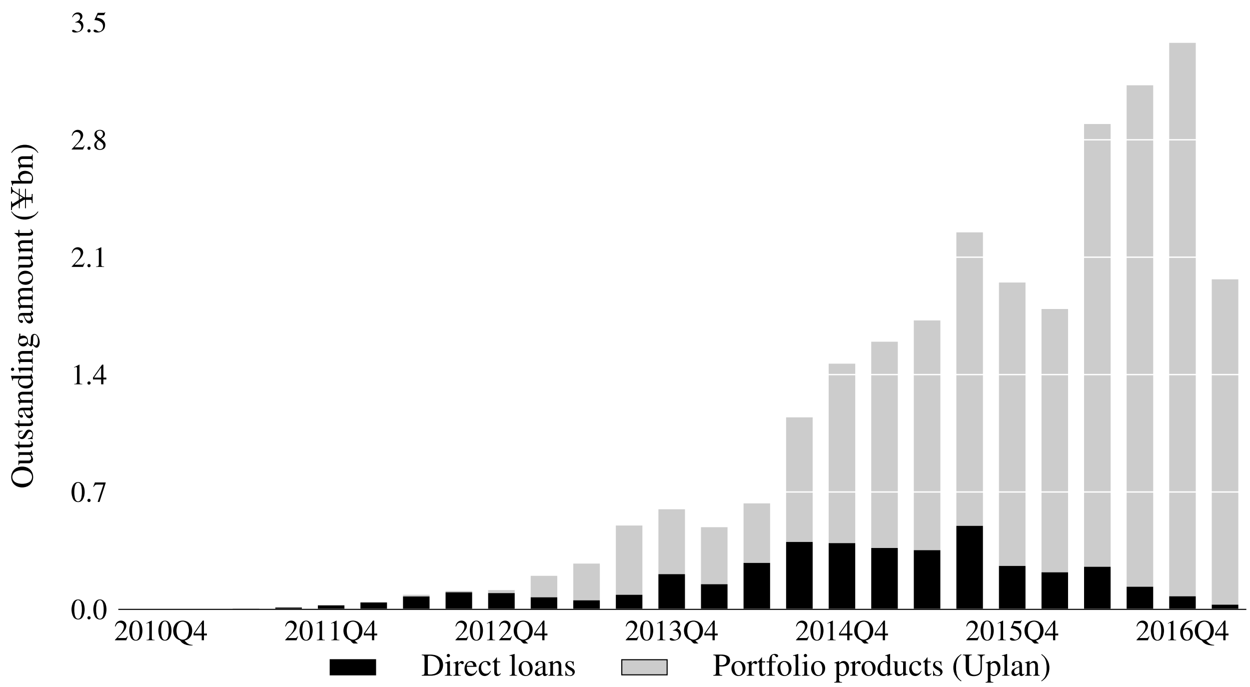


FIGURE 1. DIRECT AND MARKETPLACE LOANS AT RENRENDAI, 2010Q4–2017Q1

Figure 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 model, 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

[7]The loan is sold at a fixed price of ¥1 for each ¥ of loan amount.

[8]In addition to Uplan, Renrendai offers another portfolio product called Salary Plan (薪计划), similar to Uplan, but with a fixed 12 months maturity and investment in fixed monthly installments rather than a lump sum. Investing in Uplan or Salary Plan involves a 90–day lock–up period. It is possible for lenders to withdraw their investment before the end of the lock–up period, but this requires the payment of a 2% fee; moreover, the lender only receives a payment once Renrendai has placed the underlying loans on the secondary market.

total investment at the end of our sample period in February 2017. That reflects a general trend in the sector, which has largely moved to the marketplace model, in China as well as in Europe and the U.S. (Balyuk and Davydenko 2019). We build on this stylized fact, and investigate the welfare effects of the new business model in comparison to alternative platform designs.

B Data; loan applications, funded loans, and portfolio products

Our data cover 955,405 loan applications and 376,219 loans over the 2010–2017 period, associated with 358,383 borrowers and 351,333 lenders on Renrendai.[9] They report detailed information on loan applications, funded loans, portfolio products, and borrower characteristics, as well as individual lender IDs. Table 1 presents descriptive statistics for loan applications and funded loans. Around 40% of loan applications ultimately obtain funding. The median loan funded on the platform has size about ¥62,000 ($9,000) and maturity 36 months, and it pays a 10.8% annual interest rate. Table 1 also reveals that the median loan is financed by 45 lenders (either directly or through Uplan), and it is fully funded in about 30 seconds.

To reduce computational complexity in the estimation discussed below, we aggregate these data along some key dimensions. For both new and resale loans we create loan categories based on: (i) eight loan amount groups, ranging from ¥1,000–5,000 for the smallest to ¥100,000–300,000 for the largest; (ii) four maturity groups (1–6, 6–15, 15–24, and 24–48 months); (iii) seven interest rates groups; and (iv) two borrower creditworthiness classes (AA and A–or–below).[10] For resale loans the amount is defined by the portion of the initial loan that is sold on the secondary market, whereas the maturity is classified as the leftover duration of the loan at the time of resale. As a result, we have 219 loan categories for new and 239 for resale loans (although not all categories are populated every day in our sample).

Table 2 provides descriptive statistics for the portfolio products sold on Renrendai. The median

[9]These figures include only borrowers with fully funded loans; the total number of loan applicants (successful or otherwise) is 746,735.

[10]The breakdown into categories for all the measures is designed to ensure that the categories contain approximately the same number of loans. The eight loan amount groups are: 1–5, 5–10, 10–20, 20–30, 30–50, 50–80, 80–100, and 100–300 ’000s of renminbi. The seven interest rate groups are: 3–10, 10–10.5, 10.5–11, 11–12, 12–13, 13–15, 15–24.4 percentage points.

TABLE 1—SUMMARY STATISTICS, LOANS

	N. obs.	Mean	Std. dev.	P10	Median	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	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 (minutes)	376,219	1,372.21	3,229.13	3.18	221.32	4,103.72
1st to last investment (minutes)	376,219	30.80	247.10	0.03	0.47	13.1
Transactions completed	376,219	0.35	0.48	0	0	1
Transactions in progress	376,219	0.64	0.48	0	1	1
Default	376,219	0.01	0.10	0	0	0
Resale time (days)	254,402	0.11	0.18	0	0.07	0.22

Notes: 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. The number of observations is smaller for the Resale time variable, because it is only defined for loans that have been part of a portfolio product before.

TABLE 2—SUMMARY STATISTICS, PORTFOLIO PRODUCTS

	N. obs.	Mean	Std. dev.	P10	Median	P90
Target return (%)	4,892	8.15	1.50	6.00	8.50	9.60
Maturity (months)	4,892	8.53	5.94	3	6	12
Size (million ¥)	4,892	4.61	6.26	0.23	3.00	10.00
Minimum investment ('000 ¥)	4,892	4.51	4.43	0.50	1.00	10.00
Lenders per portfolio	4,892	180.23	201.35	8	114.50	438
Investment time (minutes)	4,892	1,034.97	1,467.80	21.83	694.68	2,381.63
Rollover rate (%)	4,238	9.88	13.08	0.00	0.03	29.50
Rollover amount ('000 ¥)	4,238	697.01	2,080.80	0.00	1.50	1,453.00
Resale time (days)	2,810	0.53	2.57	0.00	0.01	0.88

Notes: 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 the variable Rollover rate and amount, because portfolio products in the earlier years did not provide the rollover option. The number of observations is smaller for the variable 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.

portfolio product offers an 8.5% return, has a 6 months maturity, a total size of ¥3 million, and a minimum investment amount of ¥1,000. 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 under 10% of portfolio investments are rolled over on average. When lenders cash out their investment, we can measure the time until the portfolio share is liquidated on the secondary market, or resale time: on average, about half a day.

C Borrowers and lenders; maturity mismatch and liquidity risk

Table 3 displays descriptive statistics for Renrendai's borrowers and lenders. The average borrower is about 34 years old, male, and has a monthly gross income equal to ¥12,520 ($1,880). Annual income per capita in China is ¥25,974 ($3,900 and ¥2,165 per month), and in Beijing, the wealthiest part of the country, ¥57,230 ($8,600 and ¥4,769 per month).[11] 37% of the borrowers are homeowners, with 18% having a mortgage, and over 50% have college education. Finally, 13%

[11]The per capital income data are as of 2017; source: National Bureau of Statistics of China (中国国家统计局).

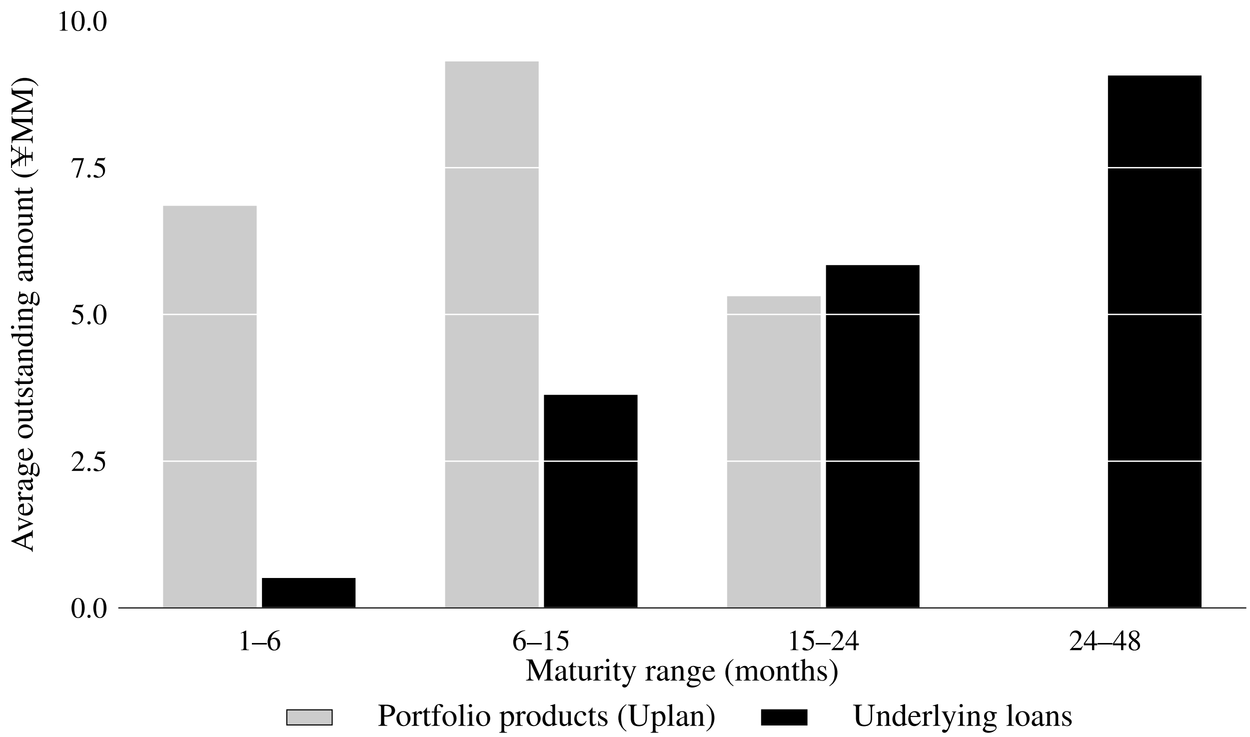


FIGURE 2. MATURITY MISMATCH ON RENRENDAI'S PORTFOLIO PRODUCTS

of borrowers are based in a "Tier 1" city (Beijing, Guangzhou, Shanghai, or Shenzhen). Taken together, these data suggest that Renrendai borrowers are part of the emerging Chinese urban middle class.

We do not observe a comparable set of demographics for the lenders, but we can reconstruct their investment history using the lender IDs. Figure 2 describes the distribution of the maturities of portfolio products and their underlying loans. On a given day, we add up the value of all outstanding portfolio products belonging to a given maturity category (1–6, 6–15, 15–24, and 24–48 months), as well as the value of all outstanding loans within a given maturity category that underlie at least one portfolio product. We average these amounts over the entire sample period and plot them in Figure 2. The most popular portfolio product have maturities under 12 months, and no portfolio exists with maturity beyond 24 months. Their underlying loans, on the other hand, have longer maturities, with the bulk of the distribution beyond 15 months. Taken together, these pieces of evidence indicate 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

TABLE 3—SUMMARY STATISTICS, BORROWERS AND LENDERS

	N. obs.	**Mean**	**Std. dev.**	**P10**	**Median**	**P90**
	(1)	(2)	(3)	(4)	(5)	(6)
A. Borrowers						
Credit rating	746,735	4.71	2.48	2	7	7
On-site verified (0/1)	746,735	0.42	0.49	0	0	1
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
Education level	669,973	1.97	0.78	1	2	3
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
First-time lenders (%)	2,299	5.20	8.11	0.54	2.82	11.32
Total daily investment (million ¥)	2,299	17.80	26.53	0.02	4.31	57.15
Daily investment ('000 ¥)	17,551,212	2.33	15.50	0.05	0.25	3.75
Total 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

Notes: 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 three variables, a day-lender for the fourth variable, and to one lender for the remaining four variables. All variables of panel A are defined in detail in Appendix A.

exclusively 24 or 36 months.

The Uplan portfolios assembled by the platform present important differences compared to the investments of direct lenders. First, their funding is much faster: The median investment time for a loan financed by direct lenders is 4.8 minutes, while for loans financed by the platform it is 0.3 minutes. Second, they are more diversified: The HHI concentration index for the average portfolio product is 2%, compared to 12% for the average direct investor portfolio. Third, they are less risky: Delinquency and default rates in portfolio products are 0.06% and 0.03%, compared to 24% and 13% for direct investors.[12] These facts are consistent with Renrendai facing lower search, diversification, and adverse selection costs in comparison to peer-to-peer investors.

The data, moreover, suggest that changes in investor population accompany the growth of Renrendai (and of debt crowdfunding in general). Between 2010 and 2017, we observe a downward trend among investor portfolios in concentration (with the HHI going from 4.3% in 2013 to 2.2% in 2016) and default rates (from 1.9% in 2013 to 0.5% in 2016), driven especially by the Uplan portfolios. That is consistent with the arrival on the platform of investors who are more focused on diversification and limiting risk than on yields; rather than picking individual loans, these lenders delegate portfolio choice to Renrendai, investing in Uplans.

We build two variables to capture those changes and reflect the increased investor heterogeneity. The first variable is 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.[13] This variable reflects 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. Second, we define a first-time lender as one who invests on the platform for the first time, and construct the daily share of first-time lenders analogously.

[12] We define a borrower as delinquent is she misses in part or in total the payment of at least one monthly installment. A borrower is in default if she/he is delinquent for at least three months in a row.

[13] In order to control for the time trend effect 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.

Descriptives for these two variables are reported in Table 3.

Table 3 also documents various interesting patterns of lenders' behavior on the platform. While on average each lender invests daily around ¥2,330, the aggregate daily average investment sums up to ¥17.8 million. The mean total investment of each lender during the whole sample period is ¥111,480, spread across 48 days of activity, investing on average in 4 portfolios and 51 loan categories. These numbers provide evidence of a substantial platform activity for each lender.

3 Model

Our model features three players: borrowers, lenders, and a debt crowdfunding platform. Borrowers post loan applications and, conditional on the loan being funded, make monthly payments. We treat borrowers as passive agents and focus on the behavior of the lenders and the platform. Lenders can invest in direct loans, or in marketplace loans by acquiring a share of a portfolio product. 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 over their investment at maturity, or cash it out facing the liquidity risk. We use a discrete choice framework to model the platform's allocation of portfolio investments across loan categories. The platform maximize its profits by choosing the target return and the degree of maturity mismatch for each portfolio product. Figure 3 illustrates a graphical representation of the model. The next paragraphs describe in detail lender and platform choices.

A Lenders

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 cashing out.

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,

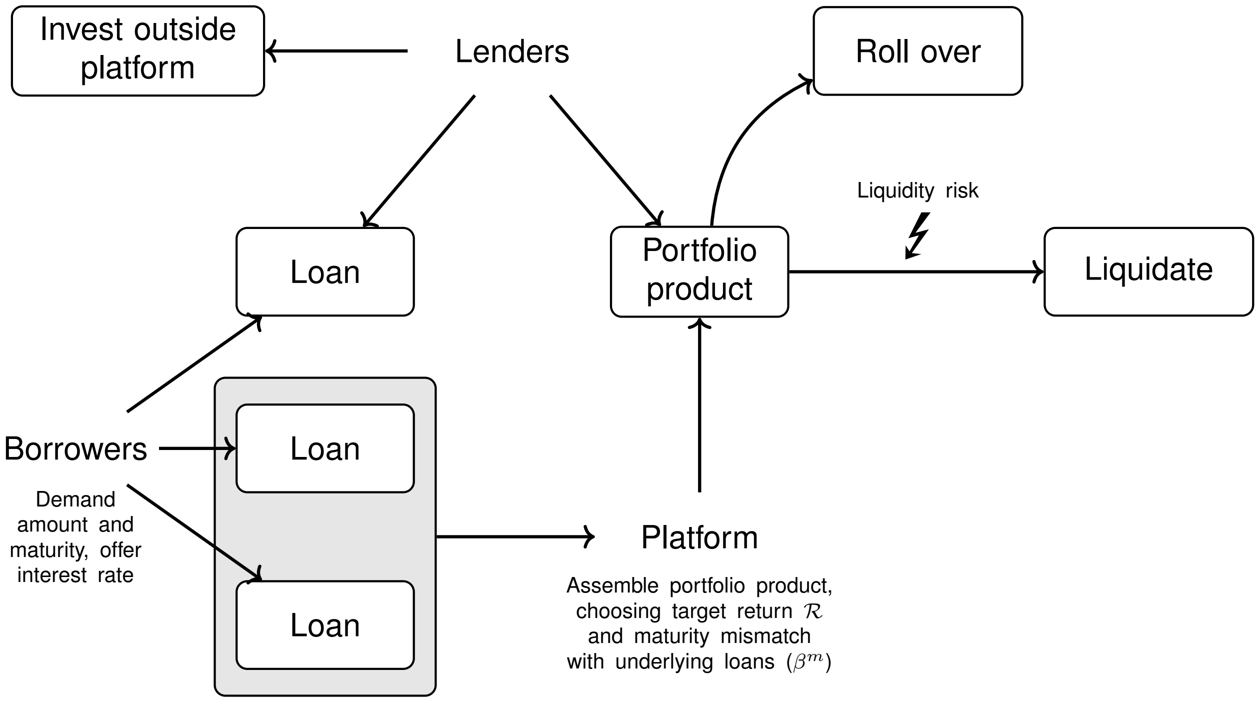


FIGURE 3. ILLUSTRATION OF THE MODEL DESCRIBED IN SECTION 3

maturity, amount, and a number of self-reported borrower attributes. In order to make the lenders' choice set computationally tractable, as discussed, 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 for direct lenders' investment on day t. A 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:

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

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). We group log-yield, log-maturity, log-amount, 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 $\delta^D_{ict} = \gamma'_{it} x_{ct} + \zeta_{ct}$.

To allow for heterogeneity in lender preferences, in equation (2) the coefficients can vary across lenders i and over time t. That helps the model capture the stylized facts described in Section 2, in particular any change in composition of the lender population towards investors with a lower tolerance for liquidity risk. At the same time, it raises the issues of how to measure lender liquidity risk tolerance and how to deal with the resulting computational complexity. As a proxy for liquidity risk tolerance, as discussed we use activity on the platform. We describe our approach to the computational complexity issue in Section 4 below.

Each lender can also invest in a portfolio product $k = 1, \ldots, K_t$ among those available on a given day t. As remarked, only very rarely we observe lenders funding portfolio products and direct loans simultaneously; we thus treat these two options as mutually exclusive.[14] The indirect utility of lender i choosing portfolio product k on day t is:

$$U^P_{ikt} = \underbrace{\alpha^{\mathcal{R}}_{it} \ln(\mathcal{R}_{kt}) + \alpha^{\mathcal{M}}_{it} \ln(\mathcal{M}_{kt}) + \alpha^{\mathcal{A}}_{it} \ln(\mathcal{A}_{kt}) + \alpha^{\mathcal{Z}}_{it} \mathcal{Z}_{kt} + \alpha^{\sigma}_{it} \sigma_{kt} + \xi_{kt}}_{\delta^P_{ikt}} + \eta_{ikt}, \qquad (2)$$

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. σ_{kt} denotes the portfolio product's liquidity, defined as the average time it takes for its underlying loans to be resold on the secondary market at maturity, or resale time. We assume that lenders have rational expectations of each portfolio's resale time. As in equation (1), the model's coefficients are allowed to vary across lenders and over time. Also as in equation (1), we group log-target return, log-maturity, log-investment amount, 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 $\delta^P_{ikt} = \alpha'_{it} \mathcal{X}_{kt} + \xi_{kt}$.

When the portfolio product reaches maturity, lenders decide whether to roll it over (at the same

[14] 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%).

conditions as they originally invested) or to cash it out. The indirect utility from rolling over is:

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

where ν_{jkt} is a normally distributed shock.

Finally, lenders have the outside option of not investing on the platform. 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 obtain a proxy for that, we assume that the day with the largest amount invested in a given quarter corresponds to the potential market size in that quarter and define that as $\mathcal{L}_t$; on a given day t, the market share of the outside option is $\mathcal{L}_t$ minus the lenders' total invested amount. We normalize the indirect utility from choosing the outside option to zero.

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

$$\mathcal{S}_{ict}^{D}(x_{ct}, \mathcal{X}_{kt} \mid \gamma_{it}, \alpha_{it}) = \frac{\exp(\delta_{ict}^{D})}{1 + \sum_{c \in C_t^D} \exp(\delta_{ict}^{D}) + \sum_{k \in K_t} \exp(\delta_{ikt}^{P})} \tag{4}$$

Similarly, the indirect utility from equation (2) determines the probability that lender i invests in portfolio product k at time t, $\mathcal{S}_{ikt}^{P}$, whose expression is analogous to equation (4); and the indirect utility from equation (3) determines the probability that she rolls over her investment in portfolio k as opposed to cashing out, $\mathcal{S}_{ikt}^{Roll}$.

B Platform

The platform's portfolio choice is treated as an asset demand model based on loan characteristics, in the spirit of Koijen and Yogo (2019). Each day t, the platform decides the features of each portfolio product $k = 1, \ldots, K_t$ that it offers, and selects the underlying loans. We assume that the loan characteristics x_{ct} defined in Section 3.A also identify the loan categories $c = 1, \ldots, C_t^P$ considered by the platform when creating portfolio products. We allow the set of loan categories available to the platform for its portfolios C_t^P to be different from those available to direct lenders C_t^D, for two reasons. First, the platform only invests in AA borrowers, which mechanically eliminates all categories with A–or–below borrowers. Second, as documented in Section 2.C, the platform is considerably faster than direct lenders at selecting the loans, and therefore might be able to fund all loans available on a certain day for some of the categories, subtracting those loan categories from the direct lenders' choice set.

The platform receives a total renminbi amount $\mathcal{L}_t \times \sum_{k \in K_t} \mathcal{S}^P_{kt}$ 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 $\mathcal{L}_t \mathcal{S}^P_{kt}$ 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}, the platform solves a portfolio allocation problem. Following Koijen and Yogo (2019), we assume that the excess returns on loan categories have a factor structure captured by their characteristics. We can then match observed portfolio weights to recover the platform's "preferences" for those characteristics, with an approach similar to the discrete-choice framework used for lender demands. 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:

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

and υ_{kct} are normally distributed demand shocks at the portfolio–loan category–day level unobserved by the econometrician. Equation (6) describes the platform's preferences for loan characteristics associated with a given portfolio product. For instance, a higher β^r indicates that the platform has a stronger preference for loans with higher yields, and these loans will constitute a larger share of the portfolio; similarly, a higher β^m indicates a stronger preference for loans with longer maturity. We let the platform have heterogeneous preferences, varying across portfolio products k and days t, for the loan characteristics that we perceive as being most relevant, that is yield and maturity. β^r_{kt} captures the platform's preference in the risk-return tradeoff between earning a greater profit margin $r_{ct} - \mathcal{R}_{kt}$, and selecting loans from borrowers with higher willingness to pay for credit, which might be a signal of low creditworthiness. β^m_{kt} instead drives the maturity mismatch in a given portfolio product, and thus determines the exposure to liquidity risk. For these reasons, we focus our analysis, and the platform's optimization problem discussed below, on these two parameters.

We also assume that the platform has an informational advantage when selecting loans relative to the individual investors, as it is able to predict the average default rate d_{ct} of a loan category c on day t. This is a realistic approximation, as the platform has access to the whole performance record of all loans ever granted, whereas individual lenders do not have this information.

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 and maturity preferences to maximize profits. On each portfolio product, the platform earns a profit Π_{kt} given by:

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

where $\mathcal{L}_t \mathcal{S}^P_{kt}$ 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. From that amount, we subtract (i) the target return $\mathcal{R}_{kt}$ paid out to lenders for a duration of $\mathcal{M}_{kt}$ years; (ii) an administrative cost $\mathcal{C}_{2kt}$ net of fees, which characterizes portfolio k and does not vary across loan categories; and (iii) a "transaction" cost $\mathcal{C}_{1kct}$, capturing the cost of locating and monitoring loans in category c.

We model $\mathcal{C}_{1kct}$ as $\beta^m_{kt} m_{ct} \overline{\mathcal{C}}_{1kt}$, where β^m_{kt} denotes the platform's preference for loans with maturity m_{ct} from equation (6), and $\overline{\mathcal{C}}_{1kt}$ is a scalar unobserved by the econometrician, but which can be recovered using the first-order conditions of the profit function as illustrated in Appendix C. We let the marginal cost $\mathcal{C}_{1kct}$ be an increasing function of the loan category maturity m_{ct}, to capture the idea that loans with longer maturities involve a longer monitoring period and therefore higher costs. Moreover, $\mathcal{C}_{1kct}$ is also an increasing function of the maturity preference β^m_{kt}, capturing the idea that when the platform has a stronger preference for longer maturity loans it exerts more screening and monitoring effort towards those loans, as they represent a larger share of its portfolio.

In equilibrium, the platform chooses portfolio product characteristics and composition so as to maximize its overall profit. Operationally, we let the platform optimally pick the target return $\mathcal{R}_{kt}$ and preference for underlying loan maturity β^m_{kt} for each portfolio product.[15] The platform solves:

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

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

4 Estimation

We estimate the model outlined in the preceding Sections to recover lender preferences for loans and portfolio products (as well as the determinants of the investment rollover decision) and the platform's preferences for loan characteristics.

Our approach builds on the logit demand for differentiated products model of Berry (1994), which obtains preference parameter estimates from market shares. We define market shares based on the probability that a given lender choose a given loan category from equation (4), and analogously for portfolio products. To account for lender preference heterogeneity, as discussed we use activity on Renrendai as an index of lender sophistication and liquidity risk tolerance. Intuitively, only lenders with deeper pockets, who have greater capacity to bear liquidity risk, can incur the minimum investment cost frequently. To aggregate this measure across all lenders in equation (4), we focus on the percentage of active lenders (in the top 5% of the active investing distribution in a given calendar quarter) among all investors who operate on the platform on a given day t; we

[15] As discussed in Section 2, we observe little variation in portfolio product maturity $\mathcal{M}_{kt}$ and target size $\mathcal{A}_{kt}$ in the data; we thus take them as given.

denote this measure by $\mathcal{E}_t$, and interpret it as the probability that a given lender is an active lender. We can thus write the coefficients in equations (1) and (4) as $\gamma_t = \bar{\gamma} + \varsigma\mathcal{E}_t$, dropping the j, where $\bar{\gamma}$ captures the preference of the most inactive lenders, while ς measures the deviation from that baseline level driven by a higher probability of being an active lender.

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:

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

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

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

$$\ln(\mathcal{S}^P_{kt}) - \ln(\mathcal{S}_{0t}) = \alpha^{\mathcal{R}}_t \ln(\mathcal{R}_{kt}) + \alpha^{\mathcal{M}}_t \ln(\mathcal{M}_{kt}) + \alpha^{\mathcal{A}}_t \ln(\mathcal{A}_{kt}) + \alpha^{\mathcal{Z}}_t \ln \mathcal{Z}_{kt} + \alpha^{\sigma}_t \sigma_{kt} + \mu_P + \mu_t + \xi_{kt} \tag{10}$$

where $\mathcal{R}$ denotes the portfolio's target return, $\mathcal{M}$ its maturity, $\mathcal{A}$ the target size of the portfolio, and $\mathcal{Z}$ collects other observable attributes of the portfolio. We also include liquidity risk σ_{kt} (time to resale associated with portfolio k on day t) in equation (10), as the lender's payoff at maturity depends on the ability to liquidate the loans in her portfolio on the secondary market. μ_P is an indicator for the portfolio channel, μ_t are day fixed effects, and ξ_{kt} are shocks. We estimate equations (9) and (10) jointly.[16]

[16]We could estimate this model in two alternative ways. First, we could exploit the individual lender-day level data to estimate a mixed logit model as in Train (2009). We avoid this option to contain dimensionality, due to the very large number of observations we have for each lender, and because it would be difficult to identify individual lenders' choice of an outside option. Second, we could estimate a random coefficients logit demand model with aggregate market shares in the spirit of Berry et al. (1995) by exploiting the empirical distribution of lender-specific level of activity on the platform, rather than aggregating their activity at the daily level. We do not consider this approach as it would increase the computational complexity, since we would not have a closed form solution for the market shares, and because our strategy already captures a similar degree of heterogeneity in lenders' preferences. In fact, while the Berry et al. (1995) approach relies on the variation in the distribution of lenders' activity over time for identification, yielding estimates of the mean and standard deviation of preferences' distributions, our simpler approach relies on

We estimate the determinants of rollover 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 $\mathcal{S}_{kt}^{Roll}$:

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

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 equations (9) and (10), but with one important difference. The 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 need to normalize all δ_{kct} with respect to one of the alternatives within portfolio k at day t. This leads to the following specification:

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

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 υ_{kct} are shocks.

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. Lender utility is an increasing function of yields for direct loans (Table 4, column (1)) as well as for portfolio products (Table 4, column (2)), even more so when there are more active lenders on Renrendai. Moreover, lenders investing in direct loans have a stronger sensitivity to returns than marketplace investors. As a gauge for that, we look at the estimates of the elasticity of demand with respect to loan and portfolio returns reported

the variation fn the mean of the distribution of lenders' activity over time, delivering estimates of baseline preference parameters and of deviations from this baseline.

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% higher return increases the demand for a given loan category by 4.6% on average; in comparison, a 10% higher target return raises portfolio product demand on average by only 3.6%.

We find that lenders prefer larger loans and portfolios, and their preference does not depend on their level of activity on the platform. Similarly, direct lenders prefer longer maturities with no heterogeneity depending on activity. On the other hand, lenders investing in portfolio products favor shorter portfolio maturities, and the more so the more active they are on the platform. Although in general lenders do not favor a longer resale time, i.e. they are averse to liquidity risk, active investors are less averse. The corresponding demand elasticity is reported in the second row of Table 5; on average, a 10% increase in resale time σ reduces portfolio product demand by nearly 22%. However, that same 10% increase in resale time reduces demand from less active lenders (10^{th} percentile) by almost 33%, while it reduces demand from more active lenders (90^{th} percentile) by just over 8%. In sum, these results are consistent with substantial lender heterogeneity. Less active lenders display a strong preference for liquidity and a weak sensitivity to returns, whereas more active lenders exhibit more appetite for yield and a weaker aversion to liquidity risk.

The estimates of the platform's demand for loan categories are summarized in Table 6 and Figure 4. Table 6 shows that on average the platform favors loans offering lower returns and longer maturities. We interpret this result as suggesting that both interest rates and maturities set by borrowers may serve as a signaling device. Riskier borrowers offer high interest rates and shorter maturities as they may struggle to obtain funding otherwise. Under that view, our result indicates that the platform prefers to fund higher quality/safer borrowers.[17] Interestingly, that contrasts with the behavior of direct lenders, who favor higher returns as we discussed. These findings are consistent with what reported in the descriptive evidence, showing that Renrendai achieves a better selection of loans vis-à-vis retail investors. This interpretation is corroborated by the results in Table 6, which show that the platform avoids loan categories with higher default

[17]This finding is reminiscent of the results of Kawai et al. (2016), who focus on adverse selection in marketplace credit. As in their paper, our results suggest that interest rates signal borrower creditworthiness. Additionally, our results are consistent with maturity being another signal of borrower creditworthiness.

TABLE 4—LENDERS' DEMAND FOR PORTFOLIO PRODUCTS AND DIRECT LOANS

	Direct	**Portfolio Product**
$\bar{\gamma}^R$- Log Return ($\mathcal{R}_{kt}$, r_{ct})	0.30***	0.27*
	(0.08)	(0.14)
ς^R - Log Return ($\mathcal{R}_{kt}$, r_{ct}) $\times$ Active lenders % ($\mathcal{E}_t$)	2.88**	2.25*
	(1.18)	(1.16)
$\bar{\gamma}^M$ - Log Maturity ($\mathcal{M}_{kt}$, m_{ct})	0.27***	0.02
	(0.02)	(0.04)
ς^M - Log Maturity ($\mathcal{M}_{kt}$, m_{ct}) $\times$ Active lenders % ($\mathcal{E}_t$)	0.23	–0.63***
	(0.22)	(0.24)
$\bar{\gamma}^A$ - Log Amount ($\mathcal{A}_{kt}$, a_{ct})	0.52***	0.99***
	(0.01)	(0.03)
ς^A - Log Amount ($\mathcal{A}_{kt}$, a_{ct}) $\times$ Active lenders % ($\mathcal{E}_t$)	0.11	0.26
	(0.17)	(0.29)
$\bar{\alpha}^\sigma$ - Resale Time (σ_{kt})		–5.66***
		(2.18)
ς^σ - Resale Time (σ_{kt}) $\times$ Active lenders % ($\mathcal{E}_t$)		57.43*
		(34.46)
Portfolio product controls	Yes	
Loan category controls	Yes	
Channel f.e.	Yes	
Day f.e.	Yes	
N. obs.	88,870	
Adj. R^2	0.732	

Notes: The table reports the estimates of equations (9) and (10), jointly estimated. One observation is one day–product category (loan category or portfolio product). Portfolio product controls include indicator for two special kinds of UPlan launched in the early days of the platform called "Beginner UPlan" and "Bonus UPlan". Loan category controls include every borrowers' characteristic listed in Table 3. The standard errors, reported in parentheses, are clustered around days. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

TABLE 5—LENDERS' DEMAND ELASTICITIES WITH RESPECT TO RETURN AND LIQUIDITY RISK

	N. Obs.	Mean	Std. Dev.	P10	Median	P90
Direct Loans Return	1,798	0.46	0.06	0.40	0.45	0.53
Portfolio Return	718	0.36	0.08	0.30	0.36	0.44
Portfolio Resale Time	718	–2.19	1.07	–3.28	–2.41	–0.81

Notes: The table reports the distribution of the coefficients $\gamma_t^{\mathcal{R}} = \bar{\gamma}^{\mathcal{R}} + \varsigma^{\mathcal{R}} \mathcal{E}_t$, $\gamma_t^r = \bar{\gamma}^r + \varsigma^r \mathcal{E}_t$, $\alpha_t^{\sigma} = \bar{\alpha}^{\sigma} + \varsigma^{\sigma} \mathcal{E}_t$ depending on the distribution of $\mathcal{E}_t$, the daily proportion of active lenders on the platform.

rates.[18] Figure 4 plots the distribution of the coefficients β_{kt}^r and β_{kt}^m representing the platform preferences for returns and maturities in different days and for the different portfolio products.

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 negative relationship between maturity and rollover probability, together with the other estimates of lender and platform preferences, indicates that maturity transformation may be problematic for the platform. When they chose portfolio products, lenders have a preference for shorter maturities. But at the same time, portfolio products with shorter maturities display a stronger maturity mismatch: a higher proportion of their loans have longer maturities than the portfolio product itself. That implies that lenders need to bear more rollover risk, and more uncertainty over the resale of loans if they chose to cash out their investment.

6 Counterfactuals

In our counterfactuals, we simulate scenarios changing three key features of the platform. First, we eliminate portfolio products, thus simulating a situation where only peer-to-peer credit is available. 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

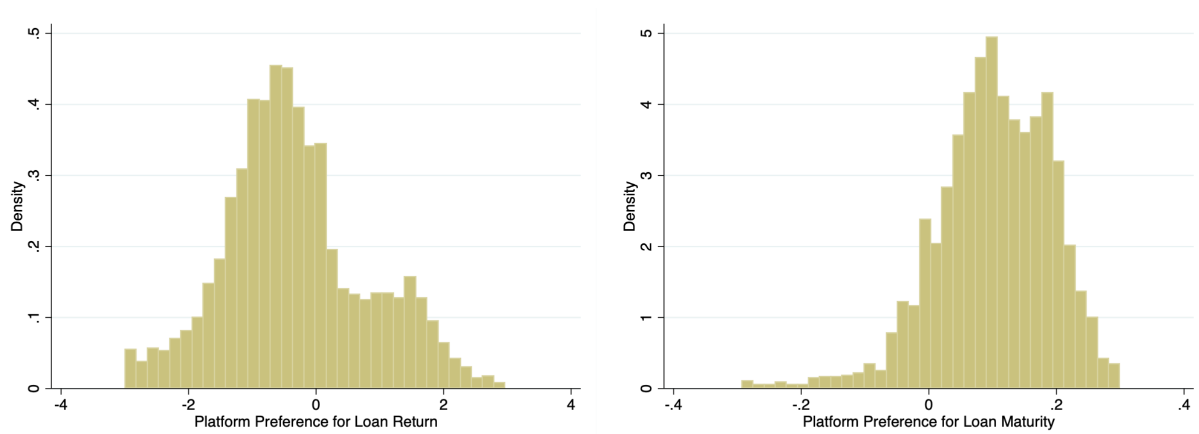
[18] Note that we use the realized default rates in each loan category up to time t. In other words, we assume that the platform can predict the average defaults in each category using the information it holds about the past records on loan performances.

TABLE 6—PLATFORM'S DEMAND FOR DIRECT LOANS

	Mean	**Standard Deviation**
Return (r_{ct})	–0.37	1.57
Maturity (m_{ct})	0.11	0.43
Amount (a_{ct})	0.87***	
	(0.09)	
Default rate borrowers (d_{ct})	–0.49***	
	(0.08)	
Share AA/A borrowers	4.42***	
	(0.36)	
Loan category controls	Yes	
Day f.e.	Yes	
N. obs.	141,727	
Adj. R^2	0.647	

Notes: The table reports the estimates of equation (12). One observation is one day–loan category. Significance levels: *** 0.01, ** 0.05, * 0.1. Standard errors in parentheses are clustered at the day level. Loan Category Controls include the variables listed in the Borrowers panel of Table 3.

FIGURE 4. PLATFORM PREFERENCES FOR LOAN RETURN (LEFT) AND MATURITY (RIGHT)



Notes: The figure reports the distribution of the coefficients β^r_{kt} and β^m_{kt} representing the platform preferences for returns and maturities in different days and for the different portfolio products.

TABLE 7—SHARE OF ROLLOVER UPLAN

Plan Return	0.015***
	(0.005)
Maturity	–0.010***
	(0.001)
Amount	0.003***
	(0.001)
Day f.e.	Yes
N. obs.	2,966
Adj. R^2	0.360

Notes: The table reports the estimates of equation (11). One observation is one day–portfolio product. Significance levels: *** 0.01, ** 0.05, * 0.1. Standard errors in parentheses are clustered at the day level. Tobit model censored below at 0 and above at 1.

two versions of this counterfactual, under baseline (i.e. relatively high) liquidity and under low liquidity. Third, we replicate the second 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 (as opposed to bank-like credit).

In the second and third counterfactuals, we modify our model to attribute liquidity risk–bearing to the platform. To that end, the profit on a given portfolio product k is now written as:

$$\begin{aligned}\Pi_{kt} = \mathcal{S}^{P}_{kt}\mathcal{L}_t \Bigg\{ & \underbrace{\sum_{c \in m \leq \mathcal{M}} w_{kct}\left(r_{ct} - \mathcal{C}_{1kct}\right) m_{ct}}_{\substack{\text{No liquidity}\\ \text{risk}}} \\ & + \underbrace{\sum_{c \in m > \mathcal{M}} w_{kct}\left(r_{ct} - \mathcal{C}_{1kct}\right)\left[m_{ct} - \left(1 - \mathcal{S}^{Roll}_{kt}\right)\frac{m_{ct}}{\mathcal{M}_{kt}}\sigma_{ct}\right]}_{\substack{\text{Liquidity}\\ \text{risk}}} - \mathcal{R}_{kt}\mathcal{M}_{kt} - \mathcal{C}_{2kt}\Bigg\}. \end{aligned} \tag{13}$$

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 equation (13). The first revenue term denotes platform's net returns on loans with maturity $m \leq \mathcal{M}$, 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 equation (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 $\mathcal{S}_{kt}^{Roll}$. 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 $1 - \mathcal{S}_{kt}^{Roll}$. In that case, the platform needs to sell her loans on the secondary market, where it may take some time before a buyer is found. The resale time comes with a loss of revenue for the platform. 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. The two cost components $\mathcal{C}_{1kct}$ and $\mathcal{C}_{2kt}$ have the same expression and interpretation as in Section 3.

The profit function in equation (13) illustrates the tradeoffs faced by the platform when setting portfolio target returns and maturity mismatch under the bank-like scenario. The platform's profits are decreasing in the return offered to the lenders; but at the same time, the portfolio product market share $\mathcal{S}_{kt}^{P}$ is increasing in the target return, and so is the rollover probability $\mathcal{S}_{kt}^{Roll}$, raising the platform's profits. Moreover, loans with longer maturities provide higher returns; but at the same time they expose the platform to more liquidity risk.

We document in Tables 8 and 9 how the outcomes predicted by our model change between the baseline case (i.e. marketplace lending, base liquidity and base proportion of active lenders) and the alternative scenarios. First, restricting credit to direct (peer-to-peer) lending induces a welfare loss. In Table 8 we show that it is associated with a 65% drop in credit provision and a 64% lower lender surplus in comparison to the baseline case.[19] That highlights the substantial benefits of platform intermediation through portfolio products, and provides a rationale for the transition to

[19]Under direct credit the platform makes no profits other than through fees, which we exclude from the analysis due to their very small magnitude and lack of data. The average daily profit for the platform under the marketplace model is around ¥1.7 bn, which would be lost under the peer-to-peer scenario.

TABLE 8—BASE LIQUIDITY: MARKETPLACE, BANK-LIKE, AND PEER-TO-PEER CREDIT

Outcome	**Marketplace**	**Bank-like**	**Peer-to-peer**
Average Return (%)	8.14	8.13	
Average Maturity Preference	0.137	0.139	
Amount Lent (bn ¥)	18.67	18.67	6.39
Amount Lent UPlan (bn ¥)	15.32	15.32	0.00
Average Change Lenders' Surplus (%)	0.00	–0.00	–63.91
Average Change Platform's Profit (%)	0.00	–0.20	

Notes: Changes are always relative to the baseline case of marketplace lending with base liquidity and base experience, whose lenders' surplus and platform's profit are normalized to zero.

the marketplace model.

Second, Table 8 shows that under base liquidity and base active lenders bank-like credit has very similar outcomes relative to marketplace credit. Credit provision levels are identical and lender surplus drops by less than 0.01% in relative terms. The platform's profits are only 0.20% lower than under the marketplace model.

The differences between the marketplace and bank-like model become more visible in Table 9, where we examine the impact of liquidity and lender population composition. In all the scenarios simulated in Table 9, we assume a longer resale time than in the baseline scenarios of Table 8, i.e. higher liquidity risk, increasing σ to 30 days. Although much longer than the baseline average time to resale of half a day, it is within the range experienced by Renrendai investors (the maximum we observe is 88 days), and well below the four months resale time that was observed in 2019 on Funding Circle, the largest U.K. debt crowdfunding platform.[20] 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.

With low liquidity, portfolio annualized target returns increase by 51 basis points under marketplace credit, whereas they decrease by over 80 basis points under the bank-like model. That

[20] "Funding Circle seeks to ease fears over withdrawal delays," *Financial Times* 11 October 2019.

happens because under the marketplace model liquidity risk makes the lenders worse off, and hence less willing to invest. That requires the platform to compensate them with higher returns. Under the bank-like model, on the other hand, it is the platform that bears liquidity risk, therefore a costly decrease in liquidity is partially passed through to the lenders via lower returns. In a similar vein, under the bank-like model the platform substantially lowers its maturity preference, reducing its exposure to liquidity risk; under the marketplace model that does not happen (if anything, maturity preference slightly increases), as in that case the platform does not bear liquidity risk. These two effects of returns and maturity preferences can also be seen in Figure 5, for the case of base active lenders. Crucially, the marketplace and bank-like models have different welfare effects for the platforms and lenders (as well as borrowers). Table 9 and Figures 7 and 6 document that marketplace credit exhibits a larger reduction in credit provision and lenders' surplus, but a smaller reduction in profits, relative to the bank-like model. In other words: with less liquidity in the secondary market, the platform prefers operating under the marketplace model, whereas borrowers and lenders would be better off under the bank-like model.

The welfare comparison changes, however, in columns (3)–(4) (as well as for the case of low active lenders in Figures 5, 7 and 6) 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 model is welfare-improving across all three dimensions: we observe greater credit provision, lender surplus, and platform profits than under the marketplace model. This result provides a rationale for the existence of marketplace credit alongside traditional banks. When liquidity risk is limited and online credit platform attract more sophisticated, less liquidity risk-averse investors, the marketplace model can be optimal. In contrast, when liquidity risk is higher or when investors are more liquidity risk-averse, traditional intermediation, corresponding to the bank-like model in our counterfactual, dominates. These observations suggest that, as debt crowdfunding becomes a more widespread investment channel and reaches a broader population of potential lenders, platforms may start offering products closer to the bank-like model.[21]

[21]Two of the largest European players, Zopa and Bondora, are examples of online platforms evolving towards this

TABLE 9—LOW LIQUIDITY: MARKETPLACE & BANK-LIKE, BASE & LOW ACTIVE LENDERS

	Base active lenders		**Low active lenders**	
Outcome	**Marketplace**	**Bank-like**	**Marketplace**	**Bank-like**
Average return (%)	8.65	7.29	8.11	6.63
Average maturity preference	0.136	0.128	0.144	0.142
Amount lent (bn ¥)	17.17	18.41	17.05	18.86
Amount lent UPlan (bn ¥)	14.21	15.04	14.00	15.25
Average change lenders' surplus (%)	–34.10	–0.43	–47.33	0.46
Average change platform profit (%)	–9.59	–12.03	–9.09	–7.75

Notes: Changes are always relative to the baseline case of marketplace lending with base liquidity and base experience, whose lenders' surplus and platform's profit are normalized to zero.

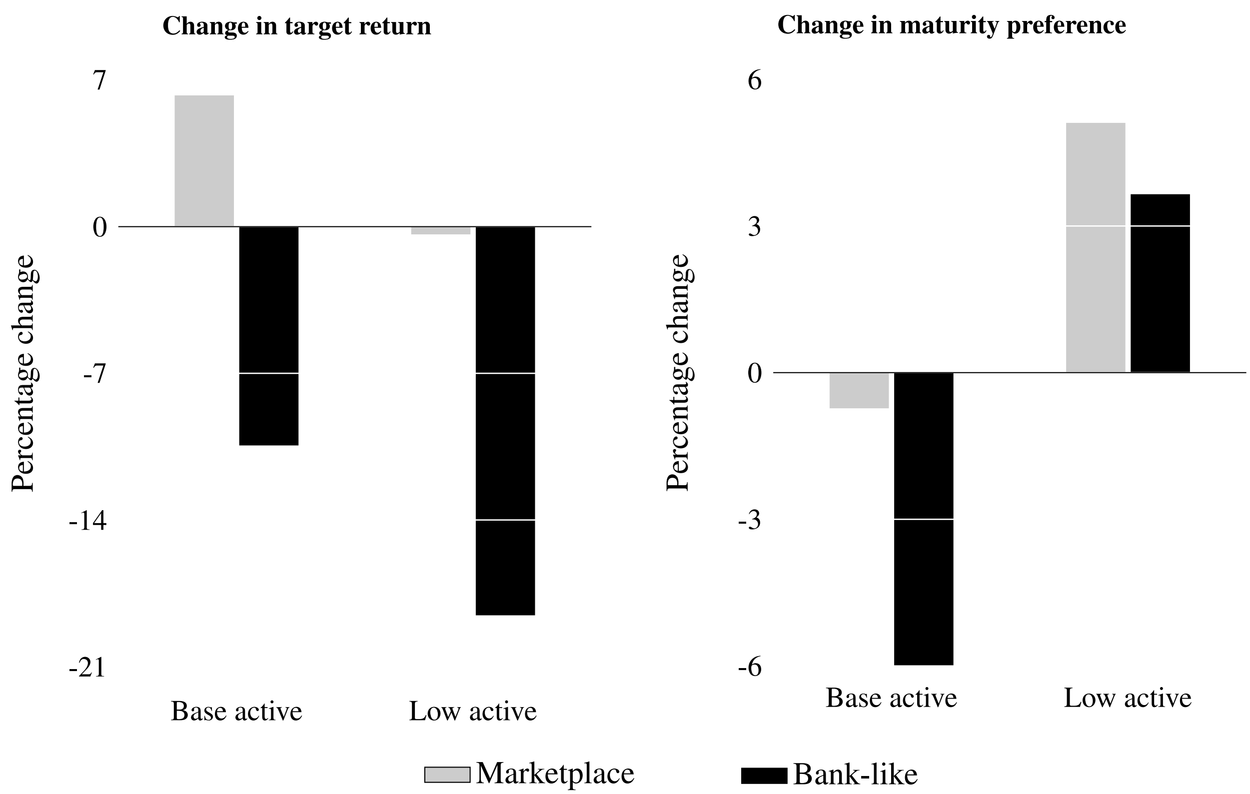


FIGURE 5. LOW LIQUIDITY—AVERAGE CHANGE RETURN & MATURITY PREFERENCE

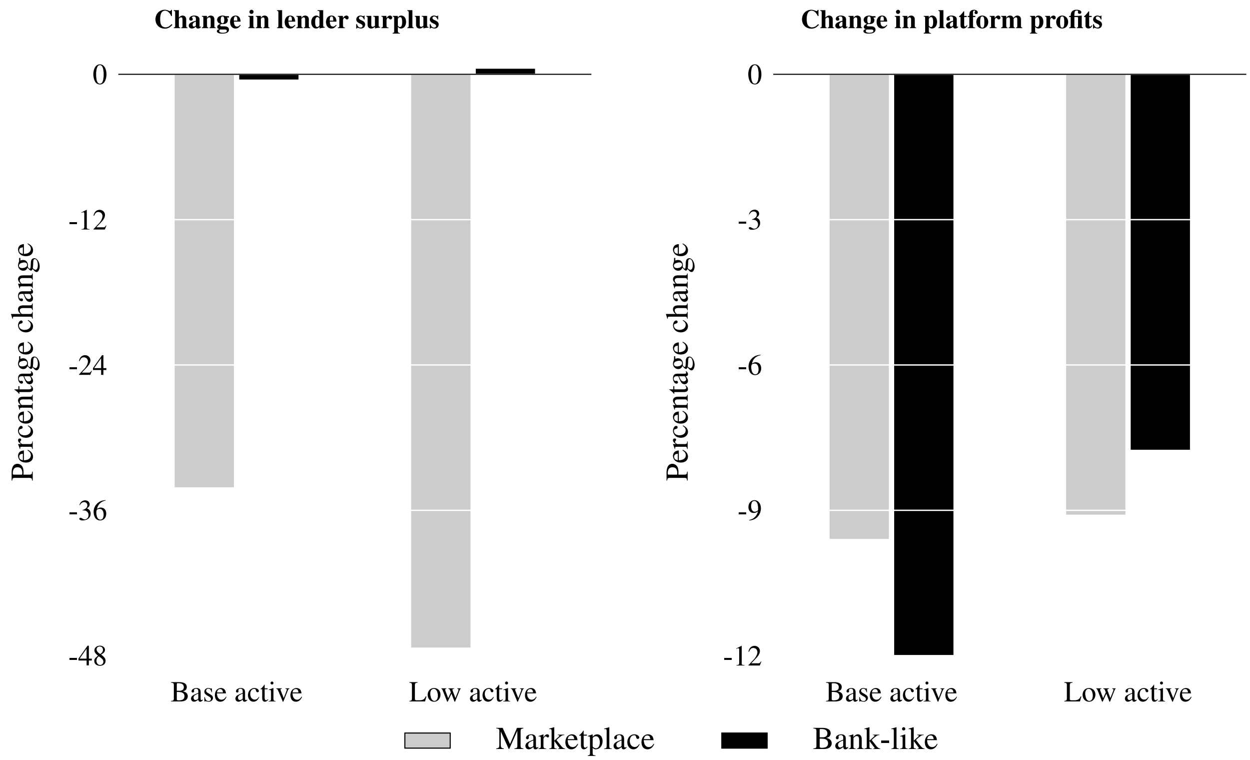


FIGURE 6. LOW LIQUIDITY—AVERAGE CHANGE LENDERS' SURPLUS & PLATFORM PROFIT

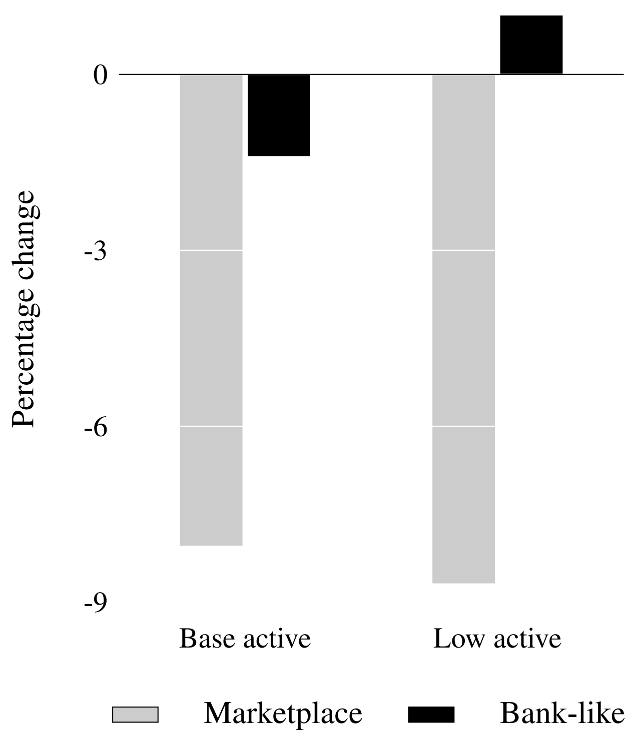


FIGURE 7. LOW LIQUIDITY—CHANGE AMOUNT LENT

7 Conclusion

We develop an equilibrium model of online debt crowdfunding to quantify the welfare effects of its marketplace credit business model, where the crowdfunding platform sells lenders a share in a loan portfolio product. That brings platforms closer to banks, because portfolio products are shorter-term liabilities invested in longer-term loans; but unlike bank depositors, marketplace lenders bear liquidity risk when they want to cash our their investment.

We estimate our model using the universe of loans and loan applications made on Renrendai, a leading Chinese marketplace credit platform. These data provide access to the information about borrowers and loans available to lenders on the platform, as well as to the full portfolio of investments held by each lender, and to the composition of the platform's portfolio products. These features allow us to draw the link between a given lender's investment and the loans that the platform makes to borrowers, helping us quantify exposure to liquidity risk. In addition, our model helps us recover lender preferences from observed investment choices, and allows us to simulate counterfactuals to contrast marketplace credit to the older peer-to-peer lending business model, and to a bank-like model where the platform bears liquidity risk.

Our results show a transition away from peer-to-peer lending and towards marketplace credit, consistent with previous findings in the literature (Balyuk and Davydenko 2019, Vallée and Zeng 2019). In comparison to prior studies, we are able to document that the shift to marketplace creates exposure to liquidity risk for the lenders, and we quantify that exposure. Moreover, we provide evidence of lender heterogeneity: less active investors on the platform are less focused on yields and more averse to liquidity risk. Finally, 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 comparison between the marketplace and the bank-like models is more ambiguous: they perform similarly in welfare terms when liquidity is high, but with low liquidity the bank-like model is preferable for

direction. Zopa recently acquired a banking license in the U.K. and is planning the introduction of fixed-term savings accounts ("P2P Lender Zopa Granted Full UK Banking License," *Financial Times* 4 December 2018). Bondora launched in 2018 a portfolio product (Go & Grow) that allows to cash out the investment at any time, using part of the profit margin to accumulate a liquidity reserve for this purpose.

lenders and borrowers (and the marketplace model for the platform). That appears to be a product of the composition of the lenders: when, in a final counterfactual, we skew the lender population towards stronger average risk aversion, the bank-like model appears preferable for the platform as well.

Our results highlight the importance of liquidity risk on debt crowdfunding platforms. They can contribute to the ongoing regulatory debate on debt crowdfunding, especially relevant as online credit platforms apply for banking licenses. Our work can also serve as a tractable starting point to explore further questions. We see as interesting extensions to our framework a model that endogenizes credit demand, as well as an appropriate quantification of differences in costs that there might be between marketplace and traditional lending, due to either technological or regulatory differences.

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Appendix For Online Publication

A Variable definitions

<u>LOAN APPLICATIONS</u>

Loan Amount (¥ ’000) Amount of the loan in remnibi

Interest Rate (%) Interest rate offered by the borrower in his/her loan application

Maturity (months) Maturity of the loan as expressed in the in the application (in months)

Financed (0/1) An indicator variable that takes the value of 1 if the loan application is fully funded by the lenders and 0 otherwise

<u>FUNDED LOANS</u>

Interest Rate (%) Annual interest rate applied to the loan

Maturity Maturity of the loan expressed in months

Number of lenders Number of lenders financing the loan

Open to 1st investment (minutes) The number of minutes between the posting time of a loan on Renrendai and the time of the first investment

1st to last investment (minutes) The number of minutes between the first and last investment in a loan

Transactions Completed Proportions of loans fully funded by the lenders and fully repaid by the borrowers

Transactions in Progress Proportions of loans fully funded by the lenders and not yet matured

Default Proportion of defaulted loans. A borrower is in default when he/she misses the payment of an installment for at least three months in a row

Resale time Number of days needed to sell a loan in the secondary market

<u>PORTFOLIO PRODUCTS</u>

Target return (%) Returns offered by a portfolio product to the lenders

Portfolio Product Maturity (months) Maturity of a particular portfolio product expressed in months

Size (’000¥) Total amount invested in a portfolio product

Minimum Investment Minimum investment necessary to acquire a portfolio product

Investment time (minutes) Time required to fund a portfolio product to its actual size

Rollover rate(%) Share of the investment rolled over by lenders at maturity per portfolio product

Rollover amount ('000 ¥) Amount rolled over by lenders per portfolio product

Resale time (days) Number of days needed to sell in the secondary market a loan funded by a portfolio product

BORROWERS

Credit Rating Credit score assigned to the borrower by Renrendai.

On-site verified (0/1) Indicator variable that takes the value of 1 if an officer from Renrendai verified that the information provided by the borrower on the internet platform is true, by visiting the borrower at her stated address.

Age Age of the borrower at the time of origination of the loan (in years).

Homeowner (0/1) Indicator variable that takes the value of 1 if the borrower owns a house and 0 otherwise.

Mortgage Indicator variable that takes the value of 1 if the borrower has an outstanding mortgage and 0 otherwise.

Monhtly income ('000 ¥) Borrower's monthly income at the origination of the loan, in RMB. Renrendai provides this information in brackets: between 0 and 1,000, between 1,001 and 2,000, between 2,001 and 5,000, between 5,001 and 10,000, between 10,001 and 20,000, between 20,001 and 50,000, and above 50,000.

Education level Highest degree of education obtained by the borrower at the time of origination of the loan.

Tier 1 city (0/1) indicator variable that takes the value of 1 if the city of residence of the borrower is Tier 1. Tier 1 cities are Beijing (北京), Shanghai (上海), Guangzhou (广州), and Shenzhen (深圳).

LENDERS

Active lenders (%) Share of active lenders investing on Renrendai in a certain day. We define a lender as active if he/she is in the top 5% of the distribution of platform use, defined as the number of times he/she invested up to that date.

First-time lenders (%) Share of first time lenders investing on Renrendai in a certain day. We define a first-time lender as one who invests on the platform for the first time.

Total daily investment (million ¥) Total amount invested by lenders on Renrendai in a day

Daily investment ('000 ¥) Amount invested in Renrendai by a lender in a day

Total investment ('000 ¥) Total amount invested by a lender in Renrendai during the sample period

Active days Number of days a lenders is active on Renrendai.

Portfolio invested Number of portfolio products a lender invests in.

Loan categories invested Number of loan categories a lender invests in.

B Data aggregation

To reduce the computational complexity, we aggregate our data based on several key dimensions. We describe below the detailed data construction procedure used to construct the dataset for models of investors' and platform's choice of direct loans.

1. *Classify loans into product categories*: Starting with borrow-level loan data, we first generate loan categories based on 4 characteristics: loan size, maturity, interest rate, and borrowers' creditworthiness. Specifically, we create 8 quantiles of loan size, 4 quantiles of loan maturity (1-6, 6-15,15-24, and 24-48 months), 7 quantiles of loan interest rates, and 2 classes of borrowers' quality (either AA and A or below). We assign a unique indicator (loan category indicator) for each of the potential combination of the 4 characteristics quantiles. We save two working datasets here. First, we save loan characteristics for each loans including information on: loan identifier, loan category indicator, loan size, maturity, interest rate, borrower's quality, the time duration in seconds between the moment when the loan becomes available to bid on the platform and the moment when the first bid is placed, the time duration in seconds between the first bid and the last bid, and some other borrower and loan characteristics. Second, we save for each unique loan category level the sub indicators of the 8 size quantiles, the 4 maturity quantile, the 7 interest rate quantiles, and the 2 borrower quality quantiles.

2. *Merge loan category information to lenders' investment on the primary market*: Using lender-borrower level data on the primary market, we merge each lender's choice of loans with loan characteristics saved from part (1), which contains each loan's loan category indicator, among other characteristics. After merging, we sum up lenders' total amount lent and take the average of all the other loan and borrower characteristics at date and loan category level. We further add to the data the four sub quantile indicators saved in part (1). After this, we obtain a dataset at the loan category and date level, containing information on the aggregated amount lenders invested in different loan categories, as well as the average borrower and loan characteristics for the primary market.

3. *Merge loan category information to lenders' investment on the secondary market*: For resale loans, the amount is defined by the portion of the initial loan that is sold on the secondary market, whereas the maturity is classified as the left over duration of the loan at the time of resale. We generate loan category indicators following the same procedure as in parts (1) and (2). We then obtain a dataset at the loan category and date level, containing information on the aggregate amount lenders invested in different loan categories, as well as the average borrower and loan characteristics for the secondary market.

4. *Combine*: Finally, we combine the datasets obtained from (2) and (3). As a result, we have 219 loan categories for new loans and 239 loan categories for resale loans. We know lenders' aggregate daily investment in these categories.

5. *Investors' choices of UPlans and Salary Plans*: Investors' choices of Uplans and Salary Plans remain at individual plan level without aggregation. In our study, we differentiate new Uplans and rolled over Uplans. After investing in a new Uplan, investors can choose to roll over this investment at the maturity. Once rolled over, a new Uplan will be generated

with a unique identifier bearing the identical characteristics. We trace the origin of rolled over Uplans. Typically, rolled over Uplans start one day after the exit date of the original Uplans with the same investor. By matching the investors' identifiers, and the exit date of the original Uplan with the beginning time of rolled over Uplans, we are able to trace the original Uplans for rolled over Uplans and compute the share of amount that is rolled over from the original Uplans.

6. *Platform's choices of loan categories via UPlans and Salary Plans*: The platform allocates funds continuously through its financial plans. Returns from previous investment will be invested again. In this part, we try to identify each financial plan's allocations, given lenders' initial investment, and do not look into continuous allocation using returns generated over time.

    - *UPlan*: The lender-borrower level data reveals the channels (via direct loans, UPlans, or Salary Plans) through which lenders invest in a certain loan, and the time of investment at the fraction of second-level precision. We merge lender-borrower level data of both the primary and the second markets, and first keep transactions financed through Uplans only. We then sort these transactions by time and UPlan identifiers. For each unique UPlan, we add up invested amount from the earliest transaction on until the cumulative amount reaches the size of UPlan. All the loans included in these transactions are supposed to belong to the platform's first choices through UPlans. After this, we obtain a dataset containing each UPlans' portfolio weights on individual loan categories. We merge to this dataset the information on individual loans' loan category indicator (from the dataset saved in part (1)), and then sum up the lent amount and take the average loan and borrower characteristics at the UPlan and loan category level. Finally, we obtain UPlan's portfolio weights on loan categories and associated average characteristics of each loan categories.
    - *Salary Plan*: We follow the same strategy as for UPlan to identify each Salary Plan's initial portfolio allocation. The difference in Salary Plans is that investors contribute to the plan every month at a fixed date for 12 times, rather than contributing with a lump-sum in the beginning as is the case for UPlan. One Salary Plan has therefore 12 rounds starting from each month's contribution day. Therefore, we treat one Salary Plan as 12 different UPlans during the one-year maturity. Every month, starting from the contribution day, we collect transactions until the cumulative lent amount reaches the contribution size of this period. Similarly, we aggregate at the date and loan category level under each Salary Plan and obtain the portfolio weights.

C Model supplemental equations

We derive two first order conditions to back out the unobserved marginal cost components $\mathcal{C}_{1kct}, \mathcal{C}_{2kt}$. The first marginal cost can be derived based on the following first order condition:

$$\begin{aligned}\frac{\partial \Pi_t}{\partial \beta^m_{kt}} =& \mathcal{S}^{UPlan}_{kt} \mathcal{L}_t \left[\sum_c \frac{\partial w_{kct}}{\partial \beta^m_{kt}} \left(r_{ct} - \beta^m_{kt} m_{ct} \overline{\mathcal{C}}_{1kt} \right) m_{ct} - \sum_c w_{kct} m_{ct} \overline{\mathcal{C}}_{1kt} m_{ct} \right] = 0 \\ \Rightarrow & \sum_c w_{kct} \left[m_{ct} - \sum_{g \in C} w_{kgt} m_{gt} \right] \left(r_{ct} - \beta^m_{kt} m_{ct} \overline{\mathcal{C}}_{1kt} \right) m_{ct} - \sum_c w_{kct} m_{ct} \overline{\mathcal{C}}_{1kt} m_{ct} = 0\end{aligned} \tag{C.1}$$

The second marginal cost can be derived based on the following first order condition:

$$\begin{aligned}\frac{\partial \Pi_t}{\partial \mathcal{R}_{kt}} =& \frac{\partial \mathcal{S}^{UPlan}_{kt}}{\partial \mathcal{R}_{kt}} \mathcal{L}_t \left[\sum_c w_{kct} \left(r_{ct} - \mathcal{C}_{1kct} \right) m_{ct} - \mathcal{R}_{kt} \mathcal{M}_{kt} - \mathcal{C}_{2kt} \right] - \mathcal{S}^{UPlan}_{kt} \mathcal{L}_t \mathcal{M}_{kt} \\ & + \sum_{j \neq k} \frac{\partial \mathcal{S}^{UPlan}_{jt}}{\partial \mathcal{R}_{kt}} \mathcal{L}_t \left[\sum_c w_{jct} \left(r_{ct} - \mathcal{C}_{1jct} \right) m_{ct} - \mathcal{R}_{jt} \mathcal{M}_{jt} - \mathcal{C}_{2jt} \right] = 0 \\ \Rightarrow & \frac{\alpha^{\mathcal{R}}_t \mathcal{S}^{UPlan}_{kt} (1 - \mathcal{S}^{UPlan}_{kt})}{\mathcal{R}_{kt}} \mathcal{L}_t \left[\sum_c w_{kct} \left(r_{ct} - \mathcal{C}_{1kct} \right) m_{ct} - \mathcal{R}_{kt} \mathcal{M}_{kt} - \mathcal{C}_{2kt} \right] - \mathcal{S}^{UPlan}_{kt} \mathcal{L}_t \mathcal{M}_{kt} \\ & - \frac{\alpha^{\mathcal{R}}_t \mathcal{S}^{UPlan}_{kt}}{\mathcal{R}_{kt}} \sum_{j \neq k} \mathcal{S}^{UPlan}_{jt} \mathcal{L}_t \left[\sum_c w_{jct} \left(r_{ct} - \mathcal{C}_{1jct} \right) m_{ct} - \mathcal{R}_{jt} \mathcal{M}_{jt} - \mathcal{C}_{2jt} \right] = 0 \\ \Rightarrow & \mathcal{L}_t \left[\sum_c w_{kct} \left(r_{ct} - \mathcal{C}_{1kct} \right) m_{ct} - \mathcal{R}_{kt} \mathcal{M}_{kt} - \mathcal{C}_{2kt} \right] - \frac{\mathcal{L}_t \mathcal{R}_{kt} \mathcal{M}_{kt}}{\alpha^{\mathcal{R}}_t} - \Pi_t = 0\end{aligned} \tag{C.2}$$

In the counterfactuals, when the platform's profit function becomes equation (13), the second first order condition becomes the following:

$$\begin{aligned}
\frac{\partial \Pi_t}{\partial \mathcal{R}_{kt}} =& \frac{\partial \mathcal{S}_{kt}^{UPlan}}{\partial \mathcal{R}_{kt}} \mathcal{L}_t \Bigg[\sum_{c \in m \leq \mathcal{M}} w_{kct} \left(r_{ct} - \mathcal{C}_{1kct} \right) m_{ct} \\
&+ \sum_{c \in m > \mathcal{M}} w_{kct} \left(r_{ct} - \mathcal{C}_{1kct} \right) \left[m_{ct} - \left[1 - \mathcal{S}_{kt}^{Roll} \right] \frac{m_{ct}}{\mathcal{M}_{kt}} \sigma_{ct} \right] - \mathcal{R}_{kt} \mathcal{M}_{kt} - \mathcal{C}_{2kt} \Bigg] - \mathcal{S}_{kt}^{UPlan} \mathcal{L}_t \mathcal{M}_{kt} \\
&+ \mathcal{S}_{kt}^{UPlan} \mathcal{L}_t \sum_{c \in m > \mathcal{M}} w_{kct} \left(r_{ct} - \mathcal{C}_{1kct} \right) \frac{m_{ct}}{\mathcal{M}_{kt}} \sigma_{ct} \tau^{\mathcal{R}} + \sum_{j \neq k} \frac{\partial \mathcal{S}_{jt}^{UPlan}}{\partial \mathcal{R}_{kt}} \mathcal{L}_t \Bigg[\sum_{c \in m \leq \mathcal{M}} w_{jct} \left(r_{ct} - \mathcal{C}_{1jct} \right) m_{ct} \\
&+ \sum_{c \in m > \mathcal{M}} w_{jct} \left(r_{ct} - \mathcal{C}_{1jct} \right) m_{ct} \left[m_{ct} - \left[1 - \mathcal{S}_{jt}^{Roll} \right] \frac{m_{ct}}{\mathcal{M}_{jt}} \sigma_{ct} \right] - \mathcal{R}_{jt} \mathcal{M}_{jt} - \mathcal{C}_{2jt} \Bigg] = 0 \\
\Rightarrow & \mathcal{L}_t \Bigg[\sum_{c \in m \leq \mathcal{M}} w_{kct} \left(r_{ct} - \mathcal{C}_{1kct} \right) m_{ct} + \sum_{c \in m > \mathcal{M}} w_{kct} \left(r_{ct} - \mathcal{C}_{1kct} \right) \left[m_{ct} - \left[1 - \mathcal{S}_{kt}^{Roll} \right] \frac{m_{ct}}{\mathcal{M}_{kt}} \sigma_{ct} \right] \\
&- \mathcal{R}_{kt} \mathcal{M}_{kt} - \mathcal{C}_{2kt} \Bigg] - \frac{\mathcal{L}_t \mathcal{R}_{kt} \mathcal{M}_{kt}}{\alpha_t^{\mathcal{R}}} - \Pi_t + \frac{\mathcal{L}_t \mathcal{R}_{kt}}{\alpha_t^{\mathcal{R}}} \left[\sum_{c \in m > \mathcal{M}} w_{kct} \left(r_{ct} - \mathcal{C}_{1kct} \right) \frac{m_{ct}}{\mathcal{M}_{kt}} \sigma_{ct} \tau^{\mathcal{R}} \right] = 0
\end{aligned} \tag{C.3}$$

D Supplemental tables

TABLE D.10—BASE VS HIGH LIQUIDITY & MARKETPLACE VS BANK-LIKE

	Base Liquidity		**High Liquidity**	
Outcome	**Marketplace**	**Bank-like**	**Marketplace**	**Bank-like**
Average Return (%)	8.14	8.13	8.13	8.14
Average Maturity Preference	0.137	0.139	0.137	0.140
Amount Lent (¥ bn)	18.67	18.67	18.70	18.67
Amount Lent UPlan (¥ bn)	15.32	15.32	15.36	15.32
Average Change Lenders' Surplus (%)	0.00	–0.00	0.17	0.00
Average Change Platform's Profit (%)	0.00	–0.20	0.01	–0.00

Notes: Changes are always relative to the baseline case of marketplace lending with base liquidity and base experience, whose lenders' surplus and platform's profit are normalized to zero.