

The Value of “New” and “Old” Intermediation in Online Debt Crowdfunding

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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 investors. We develop an equilibrium model of debt crowdfunding and estimate it on a novel database from a large Chinese platform. Moving from the peer-to-peer to the marketplace model raises lender surplus, platform profits, and credit provision. Moreover, reducing lender exposure to liquidity risk can be beneficial. A counterfactual where the platform resembles a bank by bearing liquidity risk generates larger lender surplus and credit provision 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 investment and consumer credit 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 and lender liquidity risk–aversion moderate, but improves welfare when liquidity is low and risk aversion higher.

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, 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 main difference between alternative platform designs is how large is liquidity risk and who bears it. But liquidity risk arises from a misalignment between lender, platform, and borrower horizons, so that micro data are necessary to draw the link between a lender’s investments and the loans that the platform originates to borrowers. Third, the welfare impact of platform design depends on how lender preferences trade off expected return and liquidity risk. But those preferences are intrinsically unobservable, challenging to identify, and evolving as marketplace credit reaches a larger, more heterogeneous investor pool.

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, we estimate the model and base our analysis on a new, 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 maturities to those of the underlying loans in order to quantify liquidity risk.

¹These 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 “Funding Circle seeks to ease fears over withdrawal delays,” *Financial Times* 11 October 2019.

²As 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).

Third, 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. Moreover, we have access to the entire information set observed by the lenders, attenuating the possibility that any omitted variables may bias the estimates of the lenders' preference parameters.

Our main findings are as follows. First, 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 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, consistent with a change in the platform's clientele towards investors 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. 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. We interpret this as evidence that lenders with more appetite for yield might benefit from the marketplace model, while others, more concerned about liquidity risk, might be better off under the bank-like model. We also find that Renrendai prefers to include longer-maturity, low-yield loans in its portfolio products. That is consistent with an attempt to reduce adverse selection by avoiding the riskier borrowers, in line with Stiglitz and Weiss (1981); but at the same time, it may exacerbate the maturity mismatch with the portfolio products, which have shorter maturities.

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 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: the counterfactual allowing only direct lending generates a 65% drop in credit provision and a 55% decline in lender surplus. 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 different, however, under a “stress test” scenario where we raise the time to loan resale to one month.³ Under that scenario, relative to the bank-like model the marketplace model exhibits a larger decline 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 2020) 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

³Although 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).

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 2019), 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, Onishi and Uetake 2016, Xin 2018, Tang 2020), and online marketplaces in general (Dinerstein, Einav, Levin and Sundaresan 2018, Einav, Farronato, Levin and Sundaresan 2018, Fréchette, Lizzeri and Salz 2019, Farronato and Fradkin 2018). Work in this literature has so far focused on buyers and sellers or lenders and borrowers, leaving aside an active role for platforms. In contrast, our approach directly models the design of portfolio products by the platform. This is central to our arguments and empirically relevant, as it reflects the recent shift of online debt crowdfunding from the peer-to-peer to the marketplace paradigm.

Third, our paper contributes to the literature on the value of financial intermediation. Theory work has emphasized the role of intermediaries such as banks in facilitating the provision of credit for longer-term projects via maturity transformation (Diamond and Dybvig 1983, Goldstein and Puzner 2005) and bearing the fixed costs of information collection (Diamond 1984). A recent literature attempts to assess the value of intermediation in the data: Ma, Xiao and Zeng (2020) quantify the liquidity that banks and mutual funds provide to their investors, and Drechsler, Savov and Schnabl (2020) estimate how banks manage the interest rate risk associated to maturity transformation. We contribute to this literature 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). Our results directly address the design of online credit platforms; more broadly, they allow us to quantify the wel-

fare value of the traditional functions of financial intermediation.

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 large 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 2014–2019.⁴

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), the fifth largest player in the sector in China with a 5% market share as of 2019.⁵ 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. Renrendai pre-screens loan applications, assigning a credit rating to borrowers.⁶

⁴Online debt crowdfunding in China is undergoing a restructuring driven by regulation. A number of platforms have shut down, and others may become “loan aid agencies” selling services to traditional intermediaries. The platforms that continue to intermediate credit will focus on loans to small and micro-businesses, and will lend funds raised either by securitization (similar to the marketplace model) or by issuing debt (similar to the bank-like model we discuss in Section 6). Interestingly, the liquidity risk associated with maturity transformation has been brought up as one of the targets of the reform (December 2016 Notice of the General Office of the State Council on Issuing the Implementation Plan for Special Rectification of Risks in Internet Finance, 国务院办公厅关于印发互联网金融风险专项整治工作实施方案的通知).

⁵“China’s Renrendai sees future in SMEs as P2P industry reels,” *Financial Times*, 7 January 2019.

⁶China does not have a credit registry nor an established consumer credit score comparable to the U.S. FICO score. The credit rating used on Renrendai is based on the information available to the platform, such as identity documents, phone number, employment contract, recent bank statement. The loan amount a given borrower can apply for is restricted by borrowing ceilings set by Renrendai, which depend on the borrower’s credit rating; 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

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 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 loans on Renrendai's secondary market. Marketplace lenders can choose from a menu 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. 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.⁷

Figure 1 breaks down credit at Renrendai during our sample period between di-

maturity options available to borrowers are 3, 6, 9, 12, 15, 18, 24, and 36 months. 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 about ¥345 million, corresponding to 3.2% of the value of outstanding credit-certified loans. In late 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 by China's banking regulatory commission.

⁷In 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.

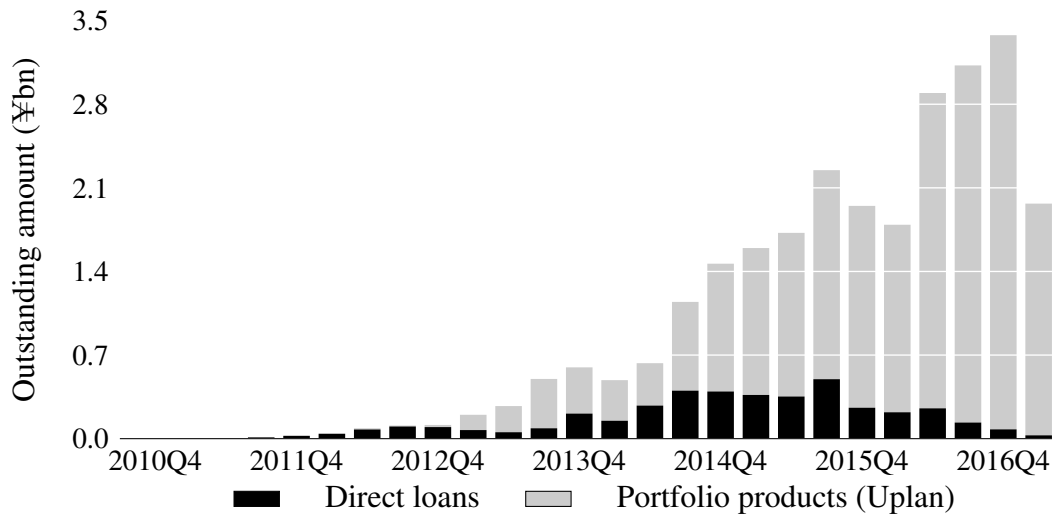


FIGURE 1. DIRECT AND MARKETPLACE LOANS AT RENRENDAI, 2010Q4–2017Q1

rect and marketplace loans. When Renrendai was first launched, online debt crowd-funding 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 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.⁸ The data 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%

⁸These figures include only borrowers with fully funded loans; the total number of loan applicants (successful or otherwise) is 746,735.

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 (conditional on being fully funded) it is originated in about 30 seconds.

TABLE 1—SUMMARY STATISTICS, LOANS

	N. obs.	Mean	St. dev.	P10	P50	P90
<i>A. Loan applications</i>						
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
<i>B. Funded loans</i>						
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
1 st to last investment (min.)	376,219	30.80	247.10	0.03	0.47	13.1
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. All variables are defined in detail in Appendix A.

To reduce computational complexity, 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).⁹ For resale loans the amount is defined by the por-

⁹The breakdown into categories for all the measures is designed to ensure that the categories

tion 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 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.¹⁰

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 long right tail, up to a maximum of 88 days. In Appendix Table D.1, we find that over 60% of the variation in loan resale time is explained by day fixed effects, whereas loan and borrower characteristics, or the daily number of lenders and borrowers active on the platform, have little explanatory power. We interpret this as evidence that liquidity risk is primarily driven by business and credit cycle conditions over which the platform has little control.

C 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 (\$1,880). Annual income per capita in China is ¥25,974 (\$3,900; ¥2,165 per

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.

¹⁰Table 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

	N. obs.	Mean	St. dev.	P10	P50	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
Min. 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	1,035	1,468	21.83	694.68	2,382
Rollover rate (%)	4,238	9.88	13.08	0.00	0.03	29.50
Rollover amount ('000 ¥)	4,238	697.01	2,081	0.00	1.50	1,453
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 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.

month), and in Beijing, the wealthiest part of the country, ¥57,230 (\$8,600; ¥4,769 per month).¹¹ 37% of the borrowers are homeowners, 18% have a mortgage, and over 50% have college education. Finally, 13% of borrowers are based in a “Tier 1” city (Beijing, Guangzhou, Shanghai, or Shenzhen). These data suggest that Renrendai borrowers are part of the emerging Chinese urban middle class.

Figure 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.¹²

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

¹²The maturity mismatch for loans made by commercial banks is comparable to what we observe

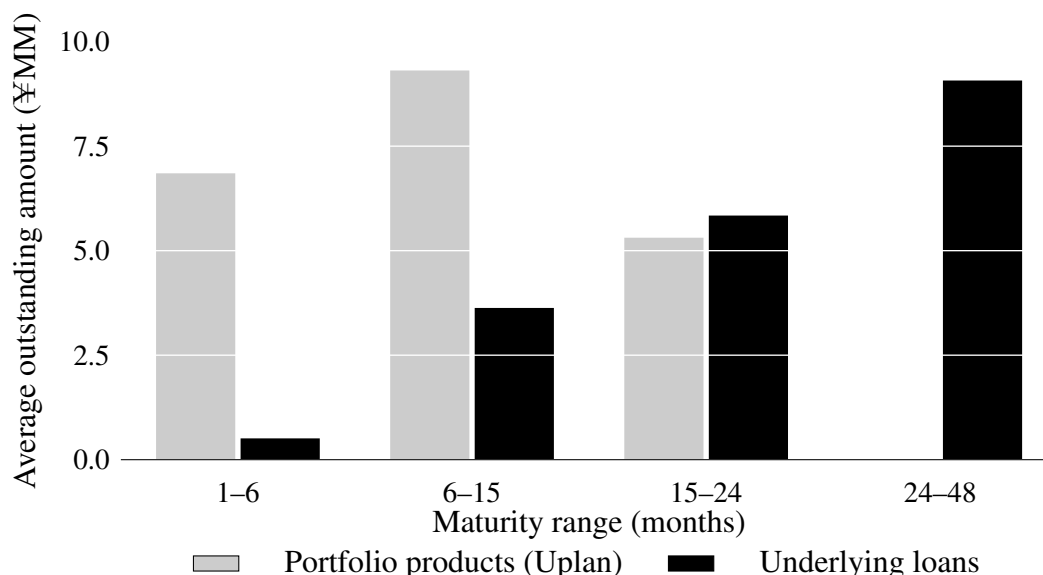


FIGURE 2. MATURITY MISMATCH ON RENRENDAI’S PORTFOLIO PRODUCTS

The Uplan portfolios assembled by the platform differ from the investments of direct lenders. First, their funding is faster: The median investment time for a loan financed by the platform is 0.3 minutes, while for loans financed by direct lenders it is 4.8 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.¹³ 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

on Renrendai. In 2015, the average maturity of loans by commercial banks in the U.S. in 2015 was 1.93 years. Aggregate deposits were on average \$10.8 Tr, and noncash payments plus ATM withdrawals were \$35.5 Tr, implying an aggregate deposit turnover rate of 3.29, and average deposit maturity of $1/3.29 = 0.30$ years. The maturity mismatch is therefore $1.93 - 0.30 = 1.63$ years, or 20 months (Sources: FRED, Federal Reserve Bank of St. Louis, and the 2019 Federal Reserve Payments Study, Table B.1). An alternative benchmark can be based on the estimates of Drechsler et al. (2020, Table A.2), who find a 2.40 years aggregate maturity for non-residential loans and a bank liabilities maturity of 0.34 years, implying a maturity mismatch of 2.06 years, or about 25 months.

¹³We define a borrower as delinquent if she misses in part or in total the payment of at least one monthly installment. A borrower is in default if she is delinquent for at least three months in a row.

TABLE 3—SUMMARY STATISTICS, BORROWERS AND LENDERS

	N. obs.	Mean	St. dev.	P10	P50	P90
<i>A. Borrowers</i>						
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
<i>B. Lenders</i>						
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

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 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.

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 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.¹⁴ 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. Descriptives for this variable are reported in Table 3.¹⁵

Table 3 also documents that on average each lender invests daily ¥2,330 and 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.

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.¹⁶ 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 their investment over 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 maximizes its profits by choosing the target return and the degree of maturity mismatch for each portfolio product. Appendix Figure D.1

¹⁴To 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.

¹⁵As 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.

¹⁶The assumption that the borrowers are not strategic is justified by the fact that nearly 80% of loan applications, and over 95% of funded loans, involve individuals active on Renrendai only once.

provides 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 $i = 1, \dots, I_t$ 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, maturity, amount, and a number of borrower attributes. In order to make the lenders' choice set computationally tractable, as discussed, we group direct loans in discrete categories $c = 1, \dots, C_t^D$, 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:

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

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 $\delta_{ict}^D = \gamma_{it}' x_{ct} + \zeta_{ct}$.

To allow for heterogeneity in lender preferences, in equation (1) the coefficients can vary across lenders i and over time t . That captures 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 a measure of the lenders' 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 $k = 1, \dots, K_t$ 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.¹⁷ The indirect utility of lender i choosing portfolio product k on day t is:

$$U_{ikt}^P = \underbrace{\alpha_{it}^{\mathcal{R}} \ln(\mathcal{R}_{kt}) + \alpha_{it}^{\mathcal{M}} \ln(\mathcal{M}_{kt}) + \alpha_{it}^{\mathcal{A}} \ln(\mathcal{A}_{kt}) + \alpha_{it}^{\mathcal{Z}} \mathcal{Z}_{kt} + \alpha_{it}^{\sigma} \sigma_{kt} + \xi_{kt}}_{\delta_{ikt}^P} + \eta_{ikt}, \quad (2)$$

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 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.¹⁸ 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 $\delta_{ikt}^P = \alpha_{it}' \mathcal{X}_{kt} + \xi_{kt}$.¹⁹

When the portfolio product reaches maturity, lenders decide whether to roll it over (at the same conditions as they originally invested) or to cash it out. The

¹⁷Out of 13,398,102 lender-date observations, we observe lenders holding both a portfolio product and direct loans in 155,604 cases (1.16%).

¹⁸We treat σ_{kt} as an exogenous portfolio attribute. We discuss this choice in Section 6.C, where we argue that our conclusions are not sensitive to it.

¹⁹A nested logit approach, with direct and portfolio investment representing the two nests, delivers very similar results as our current specification (omitted for brevity; available upon request).

indirect utility from rolling over is:

$$U_{ikt}^{Roll} = \tau^{\mathcal{R}} \mathcal{R}_{kt} + \tau^{\mathcal{M}} \mathcal{M}_{kt} + \tau^{\mathcal{A}} \mathcal{A}_{kt} + \tau^{\mathcal{Z}} \mathcal{Z}_{kt} + \tau^{\sigma} \sigma_{kt} + \nu_{ikt}, \quad (3)$$

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 proxy for that, we assume that the day with the largest amount invested in a given calendar 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 :

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

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 Kojien and Yogo (2019). Each day t , the platform decides the features of each portfolio product $k = 1, \dots, K_t$ 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 $c = 1, \dots, C_t^P$ 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 faster than direct lenders at selecting the loans, and therefore might be able to fund all loans available on a given day for some of the categories, subtracting those loan categories from the direct lenders' choice set.

The platform receives a total renminbi amount $\mathcal{L}_t \times \sum_{k \in K_t} \mathcal{S}_{kt}^P$ on day t to invest in portfolio products. That amount is allocated across portfolios based on their market shares \mathcal{S}_{kt}^P , which aggregate the individual lender demands \mathcal{S}_{ikt}^P defined in the previous section. For a given portfolio product k , the total investment amount $\mathcal{L}_t \mathcal{S}_{kt}^P$ 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 Kojien 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:

$$w_{kct} = \frac{\exp(\delta_{kct})}{\sum_{g \in C_t^P} \exp(\delta_{kgt})}, \quad (5)$$

where:

$$\delta_{kct} = \beta_{kt}^r r_{ct} + \beta_{kt}^m m_{ct} + \beta^a a_{ct} + \beta^z z_{ct} + \beta^d d_{ct} + v_{kct}, \quad (6)$$

and v_{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 most relevant loan characteristics: yield and maturity. β_{kt}^r 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_{kt}^m indicates the platform's preference for loans with long maturities in portfolio k . A larger β_{kt}^m will generate portfolios containing a larger proportion of loans with longer maturities. As a result, β_{kt}^m drives the maturity mismatch in a given portfolio product, and thus determines the exposure to liquidity risk.²⁰ 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 individual investors and is able to predict the average default rate d_{ct} . This is a realistic approximation, as the platform has access to the performance record of all loans ever granted, whereas individual lenders do not.

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:

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

where $\mathcal{L}_t \mathcal{S}_{kt}^P$ 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) a transaction cost \mathcal{C}_{1kct} , capturing the cost of locating and monitoring loans in category c ; and (iii) an administrative cost \mathcal{C}_{2kt} net of fees, which characterizes portfolio k and does not vary across loan categories.

We model \mathcal{C}_{1kct} as $\beta_{kt}^m m_{ct} \bar{\mathcal{C}}_{1kct}$, where β_{kt}^m denotes the platform's maturity mis-

²⁰We take the set of available portfolio product maturities as given, as it remains fixed throughout our data.

match parameter from equation (6), and \bar{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. The marginal cost C_{1kct} is an increasing function of the loan category maturity m_{ct} , capturing the idea that loans with longer maturities involve higher screening and monitoring costs (Calomiris and Kahn (1991)). C_{1kct} is also an increasing function of the maturity mismatch parameter β_{kt}^m , reflecting the fact that the platform will exert more screening and monitoring effort on loans that represent a larger fraction of its portfolio.

In equilibrium, 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} and preference for underlying loan maturity β_{kt}^m for each portfolio product.²¹ The platform solves:

$$\max_{\{\mathcal{R}_{kt}, \beta_{kt}^m\}} \Pi_t = \sum_k \Pi_{kt}. \quad (8)$$

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

C Equilibrium

Every day t , lenders can invest in C_t^D 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 (borrowers, on the other hand, are treated as passive). Lenders, borrowers and the platform interact in the primary or the secondary market for loans.

In the primary market, the supply of loans is exogenously given, as borrowers post loan applications involving a fixed promised interest rate, loan amount, and maturity. The demand for loans is defined by the direct lenders' market share equa-

²¹We solve the platform's optimization problem as a function of the maturity preference parameter β_{kt}^m rather than portfolio product maturity as a matter of 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_{kt}^m allows us to work with a continuous variable. Moreover, given portfolio maturity, β_{kt}^m determines the extent of maturity mismatch, so that optimizing with respect to β_{kt}^m is isomorphic to optimizing with respect to portfolio maturity.

tion (4) and the loan portfolio product weights given by equation (5). The lenders and the platform take loan promised interest rates, amounts, and maturities as given, and as a result a loan application may remain unfunded depending on the lenders' and the platform's demands.²²

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 equation (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 σ_{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 equation (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 S_{kt}^P .

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

4 Estimation

We estimate the model outlined in the preceding Sections 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 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

²²In the data, about 60% of loan applications are not funded.

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

Next, denote by \mathcal{S}_{ct}^D 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}_{ct}^D and \mathcal{S}_{0t} is linear in the preference parameters, so that we can estimate:

$$\ln(\mathcal{S}_{ct}^D) - \ln(\mathcal{S}_{0t}) = \gamma_t^r \ln(r_{ct}) + \gamma_t^m \ln(m_{ct}) + \gamma_t^a \ln(a_{ct}) + \gamma_t^z z_{ct} + \mu_D + \mu_t + \zeta_{ct}, \quad (9)$$

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 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:

$$\ln(\mathcal{S}_{kt}^P) - \ln(\mathcal{S}_{0t}) = \alpha_t^{\mathcal{R}} \ln(\mathcal{R}_{kt}) + \alpha_t^{\mathcal{M}} \ln(\mathcal{M}_{kt}) + \alpha_t^{\mathcal{A}} \ln(\mathcal{A}_{kt}) + \alpha_t^{\mathcal{Z}} \mathcal{Z}_{kt} + \alpha_t^{\sigma} \sigma_{kt} + \mu_P + \mu_t + \xi_{kt}, \quad (10)$$

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 investment channel, μ_t are day fixed effects, and ξ_{kt} are shocks. We estimate equations (9) and (10) as part of one regression model, combining lender

choices to invest in direct loans and portfolio products.²³

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}_{kt}^{Roll} :

$$\mathcal{S}_{kt}^{Roll} = \tau^{\mathcal{R}} \mathcal{R}_{kt} + \tau^{\mathcal{M}} \mathcal{M}_{kt} + \tau^{\mathcal{A}} \mathcal{A}_{kt} + \tau^{\mathcal{Z}} \mathcal{Z}_{kt} + \tau^{\sigma} \sigma_{kt} + \psi_t + \nu_{kt}, \quad (11)$$

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 issued on day t . This leads to the following specification:

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

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.

Identification of the lenders' preference parameters and the platform's demand for loans relies on the assumption that the demand shocks ζ_{ct}, ξ_{kt} , and ν_{kt} are uncorrelated with interest rates, loan amounts, and maturities, conditional on the control variables z (\mathcal{Z}) and the channel (direct loan/portfolio) and day fixed effects. A violation of this assumption could be driven by omitted variables, if the demand shocks reflect loan or portfolio product qualities that are observed only by the lenders and

²³Alternative 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.

are correlated with interest rates, loan amounts, or maturities. We rely on the institutional features of our setting to address this possibility: thanks to the level of detail of our data, we can observe exactly the same information available to the lenders. We can therefore control for every product or loan attribute that investors see when they access the platform, thus greatly reducing the scope for 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 (equations (9)–(10)) or the platform (equation (12)) and strategically adjust their loan applications. Such a degree of sophistication, however, appears 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.

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 (column 1) as well as for portfolio products (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 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 3.2%.

We find that lenders prefer larger loans and portfolios, and such preference does not depend on their level of activity on the platform. Direct lenders also prefer longer maturities, whereas portfolio product investors favor shorter portfolio maturities, the more so the more active they are on the platform.

Portfolio product investors do not favor a longer resale time, i.e. they are averse

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

	Direct loan	Portfolio product
Log Return (\mathcal{R}_{kt}, r_{ct})	0.30 (0.08)	0.23 (0.13)
Log Return (\mathcal{R}_{kt}, r_{ct}) \times Active lenders %	2.94 (1.12)	2.31 (1.11)
Log Maturity (\mathcal{M}_{kt}, m_{ct})	0.27 (0.02)	0.01 (0.03)
Log Maturity (\mathcal{M}_{kt}, m_{ct}) \times Active lenders %	0.22 (0.23)	−0.59 (0.25)
Log Amount (\mathcal{A}_{kt}, a_{ct})	0.52 (0.01)	0.99 (0.03)
Log Amount (\mathcal{A}_{kt}, a_{ct}) \times Active lenders %	0.11 (0.17)	0.24 (0.27)
Resale Time (σ_{kt})		−5.41 (2.08)
Resale Time (σ_{kt}) \times Active lenders %		53.72 (32.22)
Channel f.e.	0.85 (0.38)	1.87 (0.05)
Portfolio product controls		Yes
Loan category controls		Yes
Day f.e.		Yes
N. obs.		89,157
Adj. R^2		0.734

Notes: The table reports the estimates of equations (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 standard errors, reported in parentheses, are clustered around interactions of days, channel, and promotional portfolio products, for a total of 3,697 clusters.

to liquidity risk; however, 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 about 24.4%. However, that same 10% increase in resale time reduces demand from less active lenders (10th percentile) by about 35%, while it reduces demand from more active lenders (90th percentile) by just below 12%.²⁴ 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. We also find that standard portfolio products (Uplan) are investors' preferred investment channel, followed by direct loans. Salary plan, a portfolio product similar to Uplan but with 12-month maturity and investment in monthly installments, is the least preferred investment channel.

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

	N. Obs.	Mean	St. Dev.	P10	Median	P90
Direct Loans Return	1,798	0.46	0.06	0.40	0.45	0.53
Portfolio Return	718	0.32	0.07	0.26	0.32	0.39
Portfolio Resale Time	718	-2.44	1.02	-3.48	-2.63	-1.18

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

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

²⁴For consistency with other explanatory variables such as target return and maturity, which are expressed in annual terms, the resale time in the regression reported in Table 4 is expressed as a fraction of one year, instead of daily terms as in Tables 1 and 2.

lower interest rates and longer maturities, the platform obtains lower returns on the average loan but extends credit to a pool of safer borrowers.²⁵ Interestingly, that contrasts with the behavior of direct lenders, who, as we discussed, favor higher returns. These findings are consistent with the descriptive evidence of Section 2.B, showing that portfolio products are more diversified and have lower default rates than direct lender portfolios.²⁶ This interpretation is corroborated by the results in Table 6, which show that the platform avoids loan categories with higher default rates.²⁷ 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 very little impact on the fraction of the 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.²⁸ This is in line with the descriptive evidence of Section 2, suggesting that the platform has little ability to

²⁵Hertzberg, Liberman and Paravisini (2018), using data from the U.S. marketplace lending platform Lending Club, find that riskier borrowers self-select into longer maturities. That is due to the fact that Lending Club uses maturities to screen borrowers, by assigning higher interest rates to longer-maturity loans—in their setting, riskier borrowers are willing to pay a higher interest rate as a form of insurance against having to roll over their loan at unfavorable conditions. On Renrendai, prospective borrowers have much more flexibility when they apply for a loan, and in particular the interest rate they can offer to pay is only required to be within a broad band, so that maturity is not a screening tool.

²⁶Our interpretation of the results is that risky borrowers 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.

²⁷Note 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.

²⁸In 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 ($\text{¥}6.26$) increase in portfolio size is associated with a 6 percentage points higher rollover rate.

TABLE 6—PLATFORM’S DEMAND FOR DIRECT LOANS

	Mean	Standard Deviation
Return (r_{ct})	-0.38	1.62
Maturity (m_{ct})	0.11	0.53
Amount (a_{ct})	0.97 (0.08)	
Default rate borrowers (d_{ct})	-0.52 (0.08)	
Secondary market loan	-2.70 (0.09)	
Loan category controls	Yes	
Day f.e.	Yes	
N. obs.	137,080	
Adj. R^2	0.652	

Notes: The table reports the estimates of equation (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.

affect the secondary market for the loan (we return to this point in Section 6.C).

6 Counterfactuals

A Design of the counterfactual scenarios

We simulate scenarios changing three key features of the platform. First, we eliminate portfolio products, so that 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 two versions of this counterfactual, under baseline (i.e. relatively high) liquidity and under low liquidity. Third, we replicate

TABLE 7—ROLLOVER RATE OF PORTFOLIO PRODUCTS

Target return (\mathcal{R}_{kt})	0.93 (0.57)
Maturity (\mathcal{M}_{kt})	-0.01 (0.00)
Amount (\mathcal{A}_{kt})	0.01 (0.00)
Resale time (σ_{kt})	-0.50 (0.49)
Portfolio product controls	Yes
Day f.e.	Yes
N. obs.	2,996
Adj. R^2	0.342

Notes: The table reports the estimates of equation (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.

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 second and third counterfactuals, we modify our model to attribute liquidity risk-bearing to the platform. That involves two changes. First, the resale time variable σ is removed from the lenders’ indirect utility and rollover decision

equations. Second, the profit on a given portfolio product k is now written as:

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

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 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} from equation (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 $1 - \mathcal{S}_{kt}^{Roll}$. 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 under the marketplace model.

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.²⁹

B Results

In Tables 8 and 9 we document 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 55% lower lender surplus in comparison to the baseline case.³⁰ That highlights the substantial benefits of platform intermediation through portfolio products, and provides a rationale for the transition to 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 almost identical and lender surplus increases by 0.2% in relative terms. The platform's profits are only 0.17% 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

²⁹We implicitly assume that switching from the marketplace to the bank-like model will not change the composition of borrowers. This assumption is supported by the evidence that under the marketplace model the platform only funds highly rated borrowers, with very low default rates, through its portfolio products. Under the bank-like model, where it bears liquidity risk, the platform has no incentive to relax its lending standards, suggesting that it will fund a similar set of borrowers.

³⁰Under 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 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 (%)	8.13	8.10	
Average maturity mismatch (months)	22.30	22.30	
Amount lent (bn ¥)	19.91	19.93	6.18
Amount lent Uplan (bn ¥)	16.56	16.59	0.00
Average change lenders' surplus (%)	0.00	0.20	-54.87
Average change platform profit (%)	0.00	-0.17	

Notes: Changes are always relative to the baseline case of marketplace lending with base liquidity and base percentage of active lenders. The levels of lenders' surplus and platform's profit for the baseline case are normalized to zero.

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.³¹ 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 50 basis points under marketplace credit, whereas they decrease by over 100 basis points under the bank-like model. That 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 the liquidity risk, therefore a costly decrease in liquidity is partially passed through to the lenders via lower returns. Portfolio ma-

³¹“Funding Circle seeks to ease fears over withdrawal delays,” *Financial Times* 11 October 2019.

turity mismatch, on the other hand, adjusts very little. That makes intuitive sense, given that the distribution of maturities sought by the borrowers is stable across different scenarios, and so is the set of portfolio maturity categories offered by the platform. The behavior of target returns and maturity mismatch can also be seen in Figure 3, for the case of base active lenders.

The marketplace and bank-like models have different welfare effects for the platform, lenders, and borrowers. In columns 1–2 of Table 9, assuming the same level of lender liquidity risk–aversion as in our baseline, 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 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 (illustrated by the low active lenders case in Figures 3 and 4). 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 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 result 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 are more liquidity risk–averse, traditional intermediation dominates (corresponding to the bank-like model in our counterfactual). 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.³²

³²Two of the largest European players, Zopa and Bondora, are examples of online platforms evolving towards this direction. Zopa recently acquired a banking license in the U.K. and is plan-

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

<i>Active lenders share:</i> Outcome	Base		Low	
	Market- place	Bank- like	Market- place	Bank- like
Average return (%)	8.63	7.09	7.95	6.37
Average maturity mismatch (months)	22.30	22.20	22.30	22.20
Amount lent (bn ¥)	18.37	19.55	18.33	20.08
Amount lent Uplan (bn ¥)	15.39	16.16	15.23	16.45
Average change lenders' surplus (%)	-24.64	-0.50	-35.75	2.47
Average change platform profit (%)	-9.11	-10.44	-7.93	-5.80

Notes: Changes are always relative to the baseline case of marketplace lending with base liquidity and base percentage of active lenders. The levels of lenders' surplus and platform's profit for the baseline case are normalized to zero.

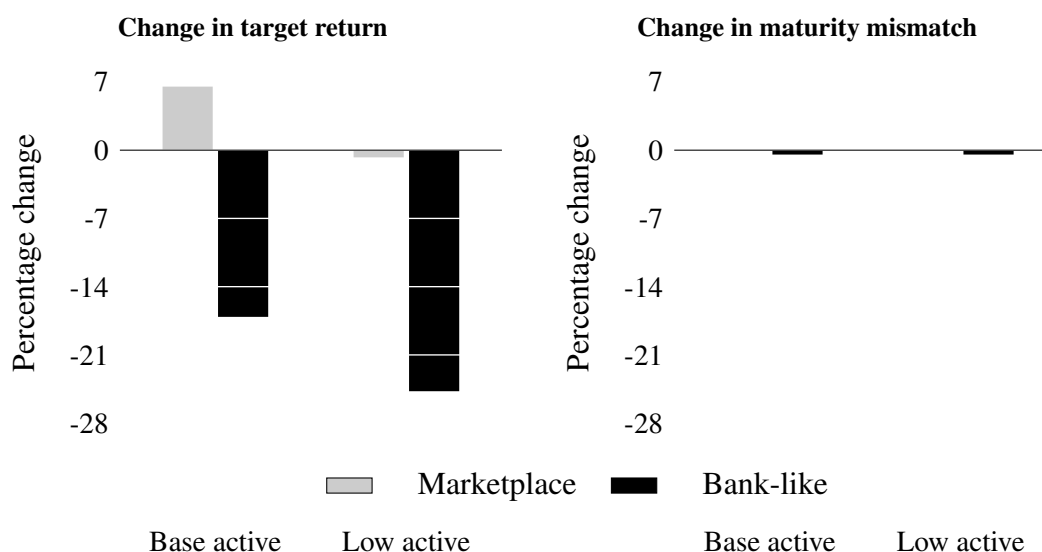


FIGURE 3. LOW LIQUIDITY: AVERAGE CHANGE IN RETURN AND MATURITY MISMATCH

ning 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 accumu-

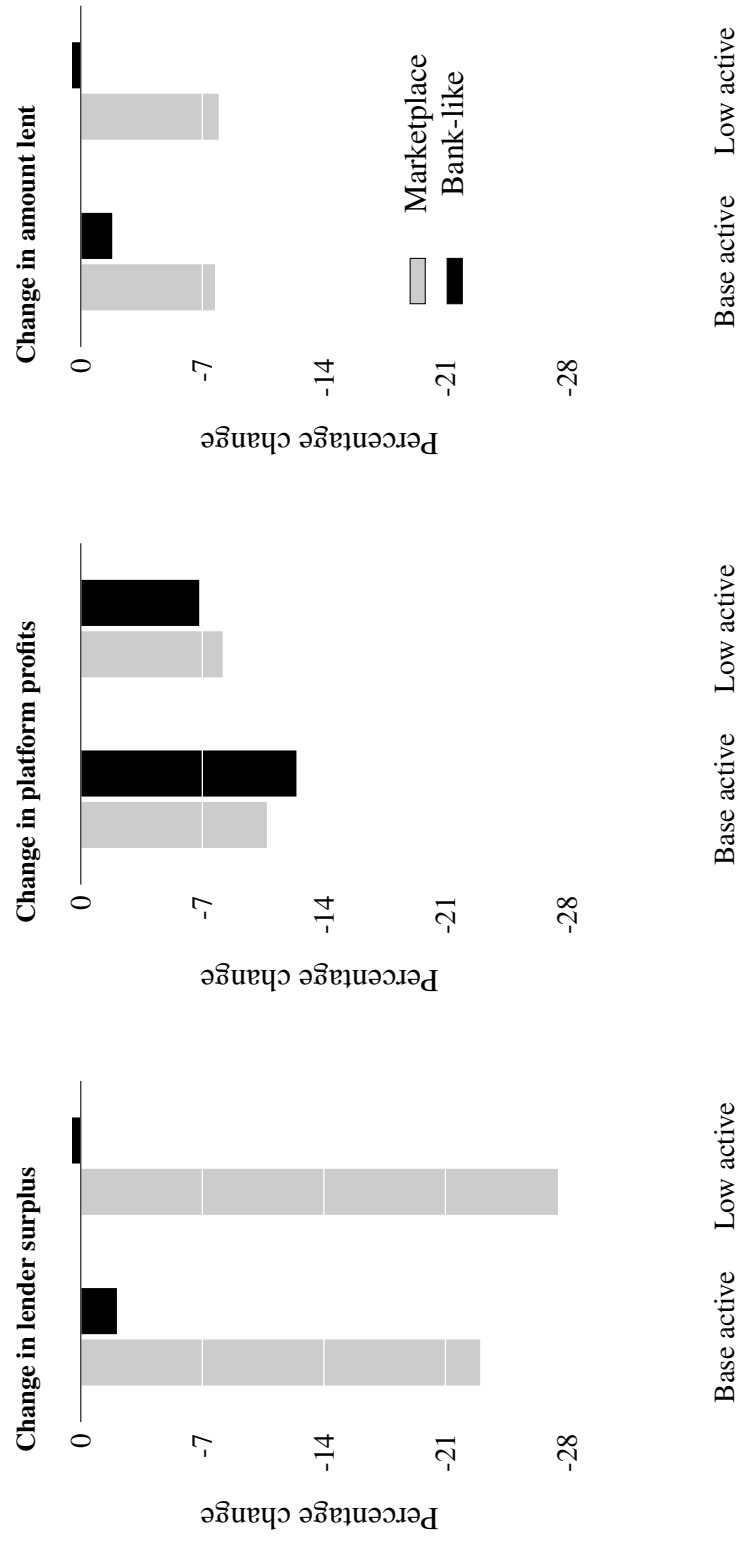


FIGURE 4. LOW LIQUIDITY: AVERAGE CHANGE IN LENDER SURPLUS, PLATFORM PROFIT, AND AMOUNT LENT

C Should resale time be endogenous?

We do not explicitly model the mechanism that determines resale time σ_{kt} , nor do we allow the platform to optimize over it. Three reasons motivate this choice. First, it is not obvious that the platform can affect resale time to begin with. The evidence discussed in Section 2 indicates that resale time is largely driven by business and credit cycle fluctuations, over which the platform has little control.³³

Second, endogenizing resale time increases the model’s computational complexity. It requires that lenders and the platform choose not only in what loans to invest, but also at what time to invest within a given day, increasing the dimensionality. In addition, portfolio resale time depends on factors that are realized at portfolio maturity, such as future demand shocks, target returns, and maturity preferences, which in turn depend on the resale time of future loans and portfolios. Treating resale time as endogenous thus gives the model a recursive nature, at the expense of tractability.

Third, endogenizing resale time is unlikely to deliver additional economic insights. Table 9 and Figure 4 indicate that, as the lender population becomes more liquidity risk-averse, the platform prefers to operate under the bank-like model, rather than the marketplace model. Suppose that the platform could optimally set σ , and consider whether that conclusion changes. Under the bank-like model, an increase in lender liquidity risk-aversion does not affect the platform’s choice of σ , because the lenders do not bear the cost of a longer resale time. Under the marketplace model an increase in lender liquidity risk-aversion creates an incentive for the platform to reduce σ , as it affects lender demands and, through them, platform profits.³⁴ Therefore, as long as reducing resale time imposes an additional cost on the platform (e.g., in terms of searching and organizing loans as represented by the term \mathcal{C}_{1kct} in equation (7)), a sufficiently high level of lender liquidity risk-aversion will induce the platform to prefer the bank-like model, thus confirming the findings

late a liquidity reserve for this purpose.

³³This is in line with the findings of Ba, Bai and Li (2019) and Li, Zhang and Zhao (2019).

³⁴Rather than reducing σ , in the marketplace model the platform could offer lenders a higher target return \mathcal{R} ; however, that will also lower the platform’s profits. Moreover, as shown in Table 5, lender preferences are more sensitive to resale time than to target returns, potentially making an adjustment based solely on target returns very costly.

of our counterfactuals.

7 Conclusion

We develop an equilibrium model of online debt crowdfunding to quantify the welfare effects of the marketplace credit business model, where the crowdfunding platform sells loan portfolio products to lenders. 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 out their investment.

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 older peer-to-peer lending paradigm and to a bank-like model where the platform bears liquidity risk.

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. 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 marketplace and bank-like models have similar welfare performance when liquidity is high and lender liquidity–risk aversion low, but the bank-like model is welfare-increasing when liquidity is low and lender liquidity–risk aversion high.

Our results highlight the importance of liquidity risk on debt crowdfunding platforms, and can contribute to the ongoing regulatory debate, 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 quantifying the differences in costs between marketplace and traditional lending, due to either technological or regulatory differences.

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For Online Publication—Appendix

A Variable definitions

LOAN APPLICATIONS

Loan Amount ('000 ¥) Amount of the loan in renminbi

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

FUNDED LOANS

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) Conditional of being fully funded, 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) Conditional on being fully funded, 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

PORTFOLIO PRODUCTS

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 rating assigned to the borrower by Renrendai. Renrendai classifies borrowers into 7 categories AA, A, B, C, D, E, HR, from the least to the most risky ones. In our sample, credit rating is 1 for AA rated borrowers; 2 for A rated borrowers; 3 for B rated borrowers; 4 for C rated borrowers; 5 for D rated borrowers; 6 for E rated borrowers; 7 for HR rated borrowers.

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.

Monthly 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.

Total investment/day (mln. ¥) Total amount invested by lenders on Renrendai in a day

Investment/day ('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 lender 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:

$$\frac{\partial \Pi_t}{\partial \beta_{kt}^m} = \mathcal{S}_{kt}^P \mathcal{L}_t \left[\sum_c \frac{\partial w_{kct}}{\partial \beta_{kt}^m} (r_{ct} - \beta_{kt}^m m_{ct} \bar{\mathcal{C}}_{1kt}) m_{ct} - \sum_c w_{kct} m_{ct} \bar{\mathcal{C}}_{1kt} m_{ct} \right] = 0$$

So that the condition is:

$$\sum_c w_{kct} \left[m_{ct} - \sum_{g \in \mathcal{C}} w_{kgt} m_{gt} \right] (r_{ct} - \beta_{kt}^m m_{ct} \bar{\mathcal{C}}_{1kt}) m_{ct} - \sum_c w_{kct} m_{ct} \bar{\mathcal{C}}_{1kt} m_{ct} = 0 \quad (\text{C.1})$$

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

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

This may be rewritten as:

$$\begin{aligned} \frac{\alpha_t^{\mathcal{R}} \mathcal{S}_{kt}^P (1 - \mathcal{S}_{kt}^P)}{\mathcal{R}_{kt}} \mathcal{L}_t \left[\sum_c w_{kct} (r_{ct} - \mathcal{C}_{1kct}) m_{ct} - \mathcal{R}_{kt} \mathcal{M}_{kt} - \mathcal{C}_{2kt} \right] - \mathcal{S}_{kt}^P \mathcal{L}_t \mathcal{M}_{kt} \\ - \frac{\alpha_t^{\mathcal{R}} \mathcal{S}_{kt}^P}{\mathcal{R}_{kt}} \sum_{j \neq k} \mathcal{S}_{jt}^P \mathcal{L}_t \left[\sum_c w_{jct} (r_{ct} - \mathcal{C}_{1jct}) m_{ct} - \mathcal{R}_{jt} \mathcal{M}_{jt} - \mathcal{C}_{2jt} \right] = 0 \end{aligned}$$

Thus the condition is:

$$\mathcal{L}_t \left[\sum_c w_{kct} (r_{ct} - \mathcal{C}_{1kct}) m_{ct} - \mathcal{R}_{kt} \mathcal{M}_{kt} - \mathcal{C}_{2kt} \right] - \frac{\mathcal{L}_t \mathcal{R}_{kt} \mathcal{M}_{kt}}{\alpha_t^{\mathcal{R}}} - \Pi_t = 0 \quad (\text{C.2})$$

In the counterfactual analysis discussed in Section 6, where the platform's profit

function is modified as equation (13), the second first-order condition becomes:

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

So that the condition is:

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

D Supplemental tables and figures

TABLE D.1—DETERMINANTS OF LOAN RESALE TIME

	(1)	(2)	(3)
Adj. R^2	0.04	0.63	0.63
Borrower characteristics	Y	N	Y
Loan characteristics	Y	N	Y
Renrendai daily market characteristics	Y	N	Y
Calendar day fixed effects	N	Y	Y
N. obs.	29,980,391	30,190,994	29,980,391

Notes: The table reports the adjusted R^2 for regressions where the dependent variable is the log-resale time (resale time is measured in days). One observation corresponds to one resale of a given loan on the secondary market. The log-resale time is regressed on borrower, loan, and daily Renrendai market characteristics in column (1); calendar day fixed effects in column (2); and both characteristics and day fixed effects in (3). Borrower characteristics include the number of loan applications, late repayment amount, number of successful loan applications, total borrowing amount, number of late repayments, number of fully repaid loans, outstanding loan amount, age, income, gender, indicators for whether the borrower is a homeowner, has a mortgage, is a car owner, has a car loan, employer's industry, employer firm size (number of employees), number of years in job position, job type, indicators for whether the borrower has a credit report, and his/her identity, job information, and income are verified, and the number of lenders financing the loan. Loan characteristics include loan amount, interest rate, maturity, indicator for high (A or AA) credit rating, loan target type (credit verified, onsite verified, guaranteed). Daily Renrendai market characteristics include the number of loans on the primary market, the number of loans on the secondary market, the amount of loans financed through direct lending on the primary market, the number direct lenders on the primary market, the amount of loans financed through portfolio products on the primary market, the number portfolio product lenders on the primary market, the amount of loans financed through direct lending on the secondary market, the number direct lenders on the secondary market, the amount of loans financed through portfolio products on the secondary market, and the number portfolio products lenders on the secondary market.

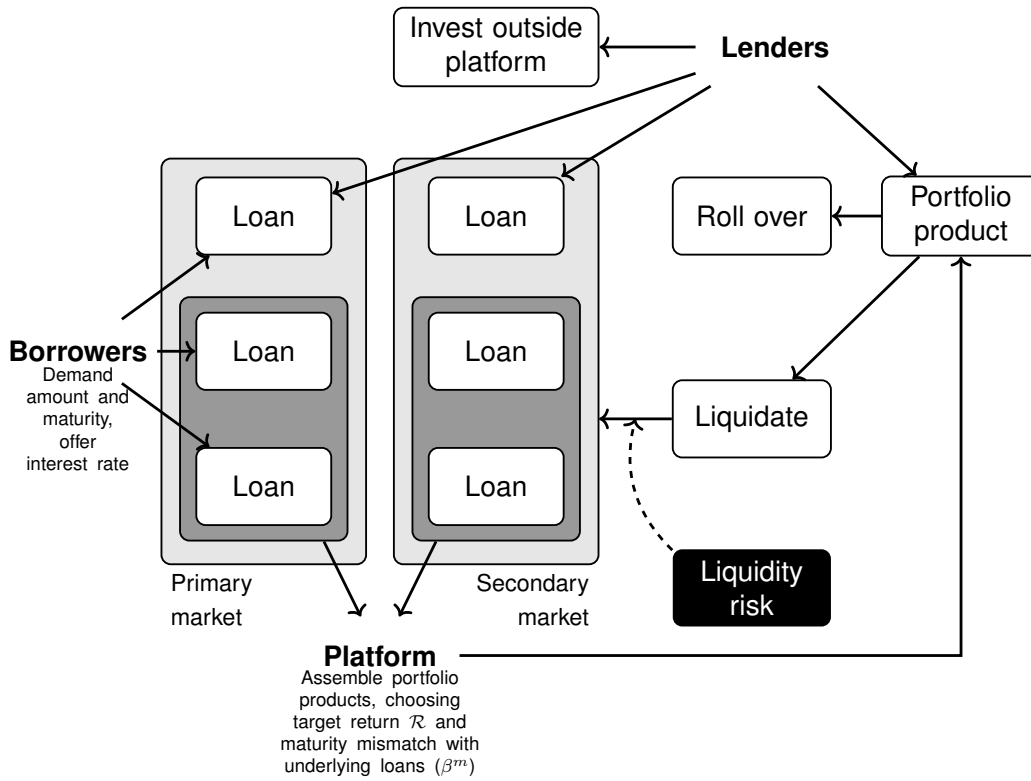
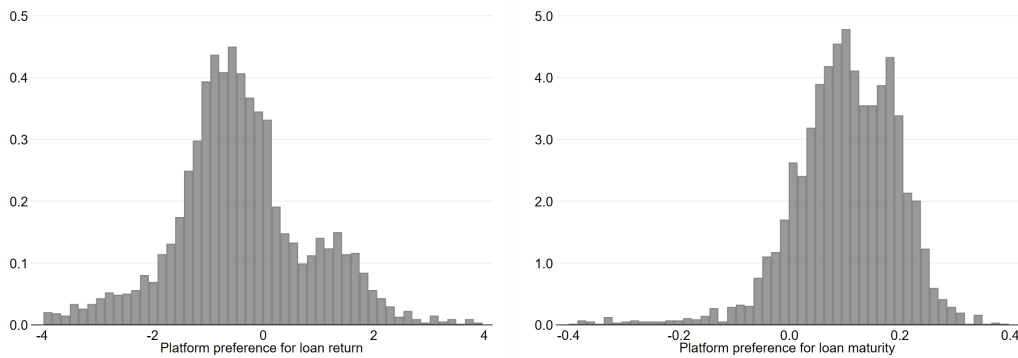


FIGURE D.1. ILLUSTRATION OF THE MODEL DESCRIBED IN SECTION 3

FIGURE D.2. PLATFORM PREFERENCES FOR LOAN RETURN AND MATURITY



Notes: The figure reports the distribution of β_{kt}^r (left) and β_{kt}^m (right), representing the platform's preferences for returns and maturities in different days and for different portfolio products.