The Value of Financial Intermediation: Evidence from Online Debt Crowdfunding

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Abstract

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

JEL classification: D14, D61, G21, G51, L21
Keywords: Financial intermediation, Marketplace credit, Structural estimation

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1 Introduction

Many online marketplaces are fundamentally peer-to-peer: the platform's focus is on matching buyers and sellers (e.g., Uber, AirBnB, eBay). In online *credit* marketplaces, on the other hand, the platform plays a much more active role, resurrecting key features of traditional financial intermediation. Debt crowdfunding platforms have moved away from the peer-to-peer paradigm and towards a new "marketplace credit" paradigm, under which they act as an intermediary by assembling loan portfolios and selling them to investors.[1] Such portfolios are characterized by maturity mismatch, as they have shorter maturity than their underlying loans. This creates liquidity risk, i.e., the risk associated with the need to refinance the loans when the portfolio matures, and raises the question of who bears it. Historically, investors have borne liquidity risk; but recently, many platforms offer "bank-like" products that more closely resemble traditional deposits, where that risk is borne not by investors, but by the platform.[2]

We ask why online credit evolved differently from other online marketplaces, and what is the welfare value of its unique features. To address these questions, we build and estimate a structural equilibrium model of online debt crowdfunding that rationalizes its development. Understanding online debt crowdfunding is important for two reasons. First, it is an increasingly relevant investment and consumer credit channel: averaging yearly growth rates well above 100%, the segment has reached $305 bn in outstanding loans worldwide in 2018 (Rau 2020). Second, online debt crowdfunding provides a clean environment to quantify the welfare value of financial intermediation in general as, in comparison to traditional intermediaries, it is exclusively focused on intermediating credit and it is less exposed to the potential confounding impact of regulation (Buchak, Matvos, Piskorski and Seru 2018).

The key forces in our model are maturity mismatch and liquidity risk. By funding longer-

[1] We use "online debt crowdfunding" as a general term encompassing alternative paradigms in online credit marketplaces. We refer to the early paradigm of debt crowdfunding as "peer-to-peer credit," and to its more recent paradigm, where the platform sells loan portfolios to investors, as "marketplace credit."

[2] In a recent SEC filing, LendingClub states that it "plans to offer a full suite of products as a bank" ("LendingClub: why boring banking is not so bad," *Financial Times*, 17 March 2021). Zopa, a U.K. platform, was granted a full 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).

maturity loans, the loan portfolios offered by the platform increase credit provision and create value for lenders, borrowers, and the platform itself. Our results indicate that the marketplace credit paradigm results in a three times larger credit provision and 50% larger lender surplus relative to peer-to-peer credit. Liquidity risk and the investors' propensity to bear it, on the other hand, affect the value created under the marketplace credit paradigm: when liquidity risk is high and investors are risk averse, bank-like products that shield investors from liquidity risk can be a welfare improvement.

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

Our main findings are as follows. First, similar to online credit platforms in the U.S. and other countries, we observe the transition 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% of the loans on Renrendai are funded as part of a marketplace loan portfolio. The key feature of these portfolios is maturity mismatch: whereas their most common maturities are 3, 6, and 12 months, the underlying loans typically mature in 36 months. The average portfolio product exhibits a degree of maturity mismatch comparable to consumer lending at traditional banks.[3] This exposes the lenders to non-trivial liquidity risk. Moreover, lender investments have become more diversified and less exposed to defaults, especially for portfolio products purchased on the platform, consistent with a change

[3]For instance, Drechsler, Savov and Schnabl (2021) find a maturity mismatch of about 25 months for non-residential loans issued by U.S. commercial banks.

in the platform's clientele towards investors that are more averse to risk.

Second, the estimates of our structural model shed light on lender preferences for loan and portfolio product characteristics, as well as on the platform's preferences for individual loan attributes when assembling portfolios. Lenders prefer higher returns, especially for peer-to-peer loans, and portfolio products with lower liquidity risk, 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 with traditional bank deposits.

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 together with 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 find that this is driven by the fact that under the marketplace model, maturity mismatch allows the platform to offer a broader assortment of portfolios, more closely tailored to the lenders' preferences; on the other hand, the platform's ability to search, screen, and monitor borrowers plays a lesser role. We also find that, with a baseline level of liquidity (time to loan resale around one-half of 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 loan resale time to one month.[4] Under that scenario, relative to the bank-like model the marketplace model

[4] Although much longer than the baseline scenario, that is well within the range experienced by lenders on Renrendai (the maximum time to resale we observe is 88 days). It is also significantly less than the four months resale

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. Finally, in a counterfactual where the lenders have weaker utility from yield and stronger disutility from liquidity risk on average the bank-like model is a Pareto improvement, raising platform profits too.

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

Our paper makes three main contributions. First, it contributes to the literature on the value of financial intermediation. Since the seminal work of Diamond and Dybvig (1983), the theory of financial intermediation points to maturity transformation as a central tool to facilitate the provision of credit for longer-term investment.[5] Empirical work in this literature has used bank-level data to develop liquidity risk indexes (Berger and Bouwman 2009, Brunnermeier, Gorton and Krishnamurthy 2012, Bai, Krishnamurthy and Weymuller 2018, Ma, Xiao and Zeng 2020) and has estimated the costs and benefits of maturity transformation (Fuster, Lo and Willen 2017, Segura and Suarez 2017, Drechsler et al. 2021), focusing on the relation between liquidity risk and financial stability. We also measure liquidity risk; but our focus is different, as we study how it affects credit provision and welfare. With our detailed data, we can construct a precise measure of liquidity risk both at the individual loan and portfolio product level and estimate lenders' preferences.

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).

[5]A second channel through which financial intermediation creates value is by bearing the fixed costs of information collection, as originally pointed out by Diamond (1984) and Holmstrom and Tirole (1997).

We are also able to simulate a rich set of counterfactual scenarios, illustrating potential conflicts of interest of the platform vis-à-vis lenders and borrowers. In addition, online debt crowdfunding constitutes a clean and tractable setting, as its business model is entirely focused on intermediating loans, and, during our sample period, it was lightly regulated.

Second, our paper provides new results on the design of online debt crowdfunding platforms. Much of the literature has focused on the information aspects of platform design: information provision to investors (Vallée and Zeng 2019), efficiency of pricing mechanisms (Franks, Serrano-Velarde and Sussman 2021), and the welfare losses associated with asymmetric information (Kawai, Onishi and Uetake 2022, DeFusco, Tang and Yannelis 2022). We take a different, complementary angle. Building on the evidence that online credit platforms increasingly offer a combination of marketplace loan portfolios and traditional bank-like products, we focus on maturity mismatch and liquidity risk, and their impact on welfare. In that respect we also relate to the literature comparing online and offline credit intermediaries (Buchak et al. 2018, de Roure, Pelizzon and Thakor 2022), 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 the design of online debt crowdfunding platforms from peer-to-peer to a combination of marketplace and bank-like credit.

Third, our paper contributes to the literature on structural estimation in financial intermediation (Egan, Hortaçsu and Matvos 2017, Crawford, Pavanini and Schivardi 2018, Wang, Whited, Wu and Xiao 2022), online credit (Kawai et al. 2022, Xin 2020, Tang 2020, DeFusco et al. 2022), 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 2022). 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.

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 was launched in 2005; it later spread to the U.S. and other large economies, reaching China in 2007 with the launch of Paipaidai (拍拍贷). China, the U.S., and the U.K. are the largest markets for online credit, accounting for about two-thirds of total lending volume (Cornelli, Frost, Gambacorta, Rau, Wardrop and Ziegler 2020). Over 2014–2019, online credit accounted for about 7.5% of total consumer credit in China.

Originally, the business model of online credit platforms involved only direct, or peer-to-peer, lending: lenders selected the loans they intended to fund and held them until maturity. Over time, two innovations emerged. First, platforms sold portfolio products, often assembled by robo-advisors. Second, they set up secondary markets, where loans can be traded, by the platform itself as well as by investors, before they reach maturity. These two features characterize a new paradigm of online debt crowdfunding, which we refer to as the marketplace model. Combined, they make maturity mismatch possible in the portfolio products: the portfolios can contain loans with longer maturity, which can be resold on the secondary market (for instance, to become part of a new portfolio product).

In the U.S., LendingClub introduced a secondary market for loans in 2008 and Prosper in 2009; in the U.K., Funding circle, RateSetter, and Zopa opened a secondary market in 2010, whereas in Continental Europe, Bondora launched it in 2013. Virtually every Chinese online credit platform offered portfolio products and set up secondary markets shortly after their establishment. A key characteristic of the marketplace credit model is that investors bear liquidity risk and may therefore have to sell at a discount and/or wait longer to liquidate their investment.

More recently, many online credit platforms have been catering to retail investors by selling bank-like savings products. In bank-like products, the investor can liquidate at any time, but the intermediary bears the liquidity risk. Marketplace portfolio products are still available, but they are targeted to institutional investors. For instance, in 2021 LendingClub acquired Radius Bank and started to offer deposit services. Zopa obtained a full banking license in December 2018, and since 2019 it has offered fixed-term savings accounts. RateSetter has been acquired by MetroBank in 2020 and now also offers traditional banking products. Funding Circle, on the other hand, did not close its secondary market, but since March 2022 it has been serving only institutional investors and has not been accepting funds from retail investors. Similarly, institutional investors on both LendingClub and Prosper can still trade loans on the secondary market and invest in portfolio products where they bear the liquidity risk.[6]

Online debt crowdfunding in China experienced a similar evolution despite recently undergoing a restructuring driven by regulation. A number of platforms have shut down, and others have become "loan aid agencies" selling services to traditional intermediaries. The platforms that continue to intermediate credit lend funds that are raised either by securitization (similar to the marketplace model) or by issuing debt (similar to the bank-like model).[7] Important for our analysis, during our sample period Renrendai is representative as it operates like most online credit platforms around the world.

B *Renrendai*

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.[8] Between its launch in 2010 and the end of our sample period in February 2017, Renrendai has had a cumulative turnover of ¥25 bn ($3.7 bn) and has registered over 1 million active users between borrower and lender accounts.

[6] LendingClub's secondary market is operating, but it is only open to institutional investors ("LendingClub Adds Client-to-Client Sales to Its LCX Automated Loan Auction Platform", LendingClub's website: https://ir.lendingclub.com/news/news-details/2022/LendingClub-Adds-Client-to-Client-Sales-to-Its-LCX-Automated-Loan-Auction-Platform/default.aspx). Prosper closed its secondary market to retail investors in 2016, but its institutional investors can still trade on it ("Prosper Closing Down Their Secondary Market for Retail Investors", FinTech Nexus News, https://news.fintechnexus.com/prosper-closing-secondary-market-retail-investors/).

[7] 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).

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

In Renrendai, users can be borrowers or lenders. Borrowers pay a small participation fee to apply for a loan on the platform.[9] When submitting a loan application, a prospective borrower specifies the amount she seeks, and proposes an interest rate and maturity. Renrendai pre-screens loan applications, assigning a credit rating to borrowers.[10] 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. Lenders pay no fees. Direct lenders fund new loans; loans that are placed on the secondary market for resale are primarily bought by the platform and become part of portfolio products.[11] 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 liquidate it. If they liquidate, the platform places the underlying loans on the secondary market, and does not bear the liquidity risk: the lenders do not receive a payment until all the corresponding loans have been resold. The loan is sold "at par," i.e., at a fixed price of ¥1 for each ¥ loaned. As the price does not adjust to market conditions, the seller may not be able to find immediately a buyer and might be forced to wait before disposing of the loan.

[9]There are no detailed data on these fees, which implies that we cannot explicitly include them in our analysis. We know however that they have been constant over the sample period and across borrowers, and very small in magnitude.

[10]China does not have a credit registry nor an established consumer credit score comparable to the U.S. FICO score. Renrendai, however, has other pieces of information that it uses as a base to develop a credit score, such as identity documents, phone number, employment contract, and recent bank statements of the borrowers. 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 (around USD 150,000). The annual interest rate has to be in the range between 7% and 24%. The maturity options available to borrowers are 3, 6, 9, 12, 15, 18, 24, and 36 months.

[11]Loans that become part of new portfolio products represent 83% of the volume of loans on the secondary market on average.

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.[12] .

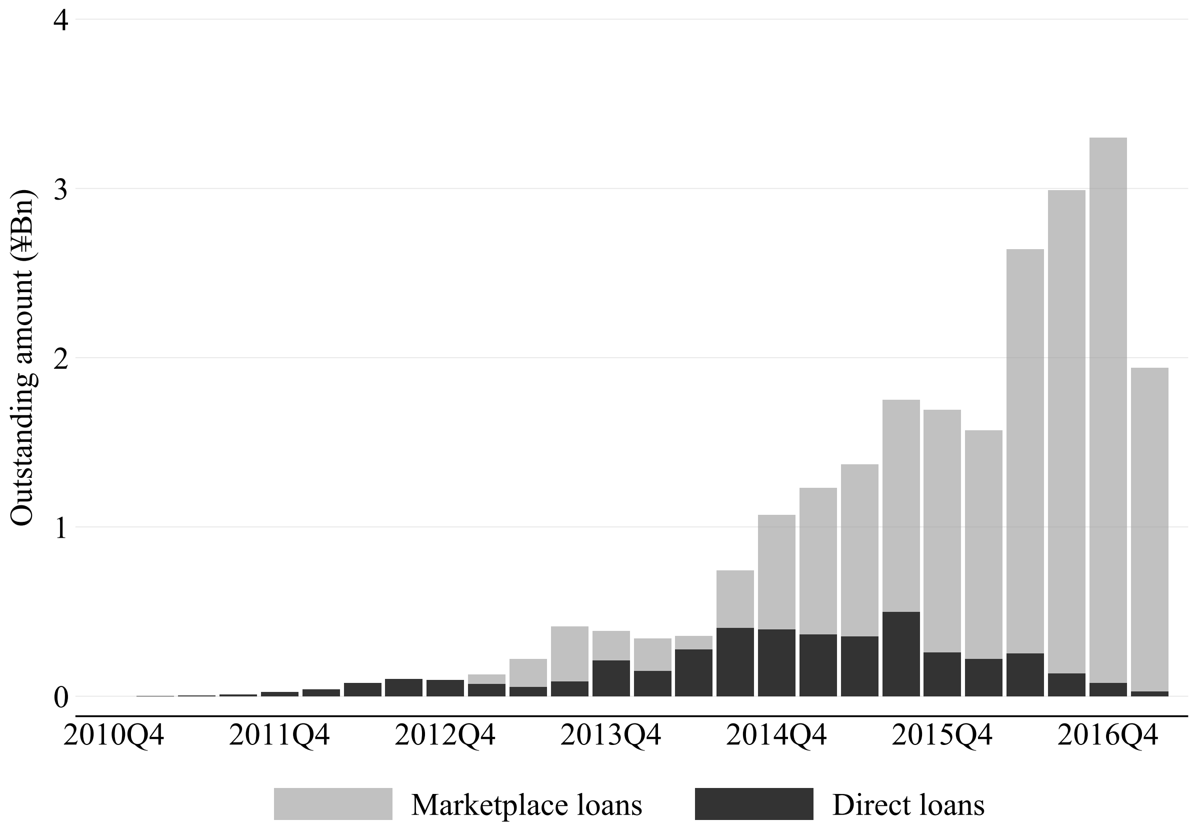

FIGURE 1. DIRECT AND MARKETPLACE LOANS AT RENRENDAI, 2010Q4–2017Q1

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

Figure 1 breaks down credit at Renrendai during our sample period between direct and marketplace loans. When Renrendai was first launched, online debt crowdfunding was based on the older peer-to-peer paradigm, and 100% of loans were direct. Portfolio investment was introduced in December 2012, and since then we observe a steady rise of marketplace credit, reaching 98% of

[12]In addition to Uplan, Renrendai offers another portfolio product called Salary Plan (薪计划), similar to Uplan, but with a fixed 12 months maturity and investment in fixed monthly installments rather than a lump sum. Investing in Uplan or Salary Plan involves a 90-day lock-up period. It is possible for lenders to withdraw their investment before the end of the lock-up period, but this requires the payment of a 2% fee; moreover, the lender only receives a payment once Renrendai has placed the underlying loans on the secondary market. Salary Plan investments are economically smaller than Uplan ones: they incorporate about 6% of all loans and 3% of their aggregate outstanding amount.

total investment at the end of our sample period in February 2017. We build on this stylized fact, and investigate the welfare effects of the marketplace credit model in comparison to alternative platform designs. In October 2020, as a result of regulatory pressure intended to curtail online lending, Renrendai experienced withdrawals and low liquidity in the secondary market. This took place over three years after the end of our sample period, and it is implausible that loans issued before March 2017 are at the root of these developments.[13]

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

Our data cover 955,405 loan applications and 376,219 loans, associated with 358,383 borrowers and 351,333 lenders on Renrendai.[14] The data report detailed information on loan applications, funded loans, portfolio products, borrower characteristics, and individual lender IDs. Table 1 presents descriptive statistics for loan applications and funded loans. Around 40% of loan applications ultimately obtain funding, and among those the average default rate is 1%. The median loan funded on the platform has size of about ¥62,000 ($9,000) and maturity of 36 months; it pays a 10.8% annual interest rate, and is financed by 45 lenders. To reduce computational complexity, we aggregate these data into categories based on loan size, maturity, interest rate, and borrower creditworthiness, defined in Appendix B.

Table 2 provides descriptive statistics for the portfolio products sold on Renrendai. The median portfolio product offers an 8.5% return, has a maturity of 6 months, a total size of ¥3 million, and a minimum investment amount of ¥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 over 12% of portfolio

[13] The available evidence indicates that the withdrawals were not driven by the fundamentals of the loans, as loans on Renrendai have always been characterized by very low default rates. The National Internet Finance Registration and Disclosure Service Platform (全国互联网金融登记披露服务平台), a regulatory body, verified data on Renrendai's borrower and loan characteristics as well as on default rates. Moreover, Renrendai has always been among the first platforms to comply with the regulator and among those with the best disclosing practices. Sources: "What is the key to the steady development of Renrendai?," *Tencent*, 15 August 2019. "Renrendai Yang Yifu: Compliant operation is the most basic capability of online lending platforms," *China Finance*, 10 May 2019.

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

TABLE 1—SUMMARY STATISTICS, LOANS

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

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. All variables are defined in detail in Appendix A.

investments are rolled over on average. When lenders liquidate their investment, we can measure the time until the portfolio share is sold on the secondary market, or resale time: on average, about half a day.[15]

The resale time of portfolio shares at maturity plays an important role in our analysis, as it captures the liquidity risk that lenders face when investing in a portfolio product. On average the secondary market for loans is liquid, but the resale time distribution has a thick right tail. Out of 2,810 portfolio products in our data, around 9.5% have resale time in excess of one day. For these cases, the mean resale time is 4.2 days and the maximum is 88 days. Note that all lenders investing in the same portfolio face the same resale time, as the platform waits until all non-rolled over loans are sold on the secondary market before liquidating lenders.

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

TABLE 2—SUMMARY STATISTICS, PORTFOLIO PRODUCTS

	N. obs.	Mean	St. dev.	P10	P50	P90
Target return (%)	3,973	8.27	1.50	6.00	8.50	10.00
Maturity (months)	3,973	8.46	5.76	1	6	12
Size (million ¥)	3,973	5.07	6.78	0.20	3.00	10.00
Min. investment ('000 ¥)	3,973	4.64	4.49	0.50	1.00	10.00
Loans per portfolio	3,971	8,767	7,982	1,475	6,908	17,916
Lenders per portfolio	3,973	286	263	62	216	603
Investment time (minutes)	3,973	1,120	1,597	14	712	2,832
Rollover rate (%)	3,383	12.34	13.57	0.00	9.20	32.67
Rollover amount ('000 ¥)	3,383	872	2,296	0.00	165	1,820
Resale time (days)	2,810	0.53	2.57	0.00	0.01	0.88

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.

D 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 month), and in Beijing, the wealthiest part of the country, ¥57,230 ($8,600; ¥4,769 per month).[16]

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.[17] Only a small portion of the

[16]The per capital income data are as of 2017; source: National Bureau of Statistics of China.

[17]The maturity mismatch for loans made by commercial banks is comparable to what we observe on Renrendai. In 2015, the average maturity of loans by commercial banks in the U.S. in 2015 was 1.93 years. Aggregate deposits

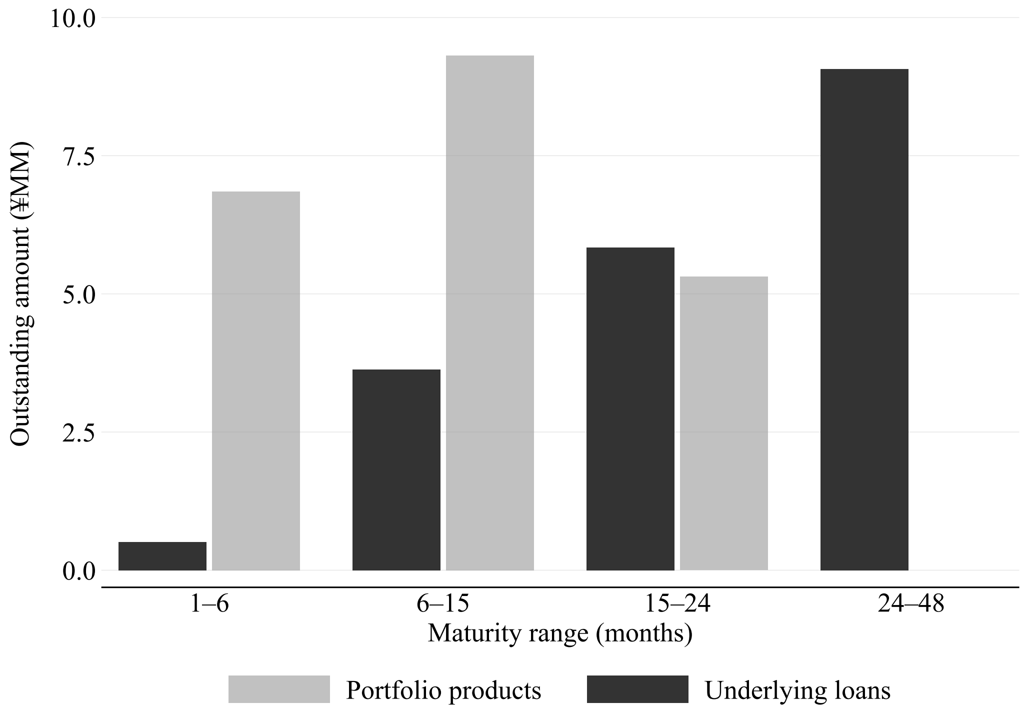

FIGURE 2. MATURITY MISMATCH ON RENRENDAI'S PORTFOLIO PRODUCTS

Notes: The figure plots the outstanding amounts of portfolio products sold by Renrendai and their underlying loans by maturity bins. The light bars represent the total outstanding amounts of portfolio products. The dark bars represent the total amount of outstanding loans underlying the portfolio products.

loans in the average portfolio product (0.14%) matures prior to the product's expiration; in those cases, the proceeds on those loans are reinvested by the platform.

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

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. (2021, 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.

TABLE 3—SUMMARY STATISTICS, BORROWERS AND LENDERS

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

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.

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.[18] This variable reflects familiarity with the platform and/or laxer financial constraints: because Renrendai requires a minimum investment amount, more frequent investments indicate that the lender has greater financial resources, and should therefore be less liquidity risk-averse. We compute the daily share of active investors as the ratio of active investors to the total number of lenders investing on the platform on a given day. Descriptives for this variable are reported in

[18]To control for the time trend in this measure, which might skew the frequency of active lenders towards the end of the sample period, we define the top 5% based on the platform use distribution within each calendar quarter.

Table 3.[19]

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 repayments. We treat borrowers as passive agents, which keeps the model tractable and helps us highlight the key drivers in the counterfactuals, where we compare marketplace credit to alternative lending paradigms. This assumption is justified by three reasons. First, default rates are low (1% on average). This suggests that, even if a change in the platform's lending model were to attract a different type of borrowers, those borrowers could be at best marginally safer than under marketplace credit.[20] Second, nearly 80% of loan applications and over 95% of funded loans are made by individuals active on Renrendai only once, who are unlikely so familiar with the platform as to condition their decisions on expected lender demand or on the platform's business model. Third, borrower characteristics do not exhibit much variation over time, particularly around 2014, when marketplace loan portfolios became the main funding channel.[21] This rules out the possibility that, even though the typical borrower interacts with the platform only once, different *types* of borrowers may approach the platform in response to a change in the lending model.

We focus on the behavior of the lenders and the platform. Lenders can invest in direct loans, or in marketplace loans by acquiring a share of a portfolio product. We model the lenders' investment decisions using a discrete choice framework, where the lenders choose among loans and portfolio products based on their characteristics. Conditional on investing in a portfolio product, lenders can decide to roll their investment over at maturity, or cash it out facing the liquidity risk.

[19]As an alternative, we replace the active lenders share by 1 minus the share of first-time platform users; the underlying assumption is that first-time users may be more risk averse. We find that it has a qualitatively similar relation to lender preferences as the active lenders share. These results are omitted for brevity but available upon request.

[20]Relatedly, from the borrowers' point of view defaulting has the same costs and benefits regardless of the platform's lending model, indicating that it is unlikely that direct lending or marketplace credit (or bank-like credit, which we discuss below) induce different degrees of borrower moral hazard.

[21]For example, borrowers' monthly income is on average ¥8,600 (USD 1,290) up to 2014 and ¥8,800 (USD 1,320) after 2014, borrowers' age is about 34 years on average both before and after 2014, and 43.37% (47.51%) of the borrowers have a college (or higher) degree up to (after) 2014.

We also 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 provides a graphical summary of the model. The next paragraphs describe in detail lender and platform choices.

A Lenders

Every day t a set of lenders $i = 1, \ldots, I_t$ can invest on the platform. Each lender can choose between investing in direct loans, identified by superscript D, or in a portfolio product, identified by superscript P; if she invests in a portfolio product, at maturity she also faces the choice between rolling over and liquidating.

In principle, lenders can choose among a large set of direct loans, either newly posted or trading in the secondary market. Those loans are differentiated by observable characteristics such as yield, maturity, amount, and a number of borrower attributes. In order to make the lenders' choice set computationally tractable, as discussed, we group direct loans in discrete categories $c = 1, \ldots, C_t^D$, which include loans that are homogeneous in terms of observable characteristics and are available for direct lenders' investment on day t. If a category has no loan applications on a given day t, then that category will not be part of the lenders' choice set on day t. Notice however that throughout the sample period there are always multiple loan categories and multiple portfolio products available for lenders on each day. Each day a lender can invest in at most one portfolio product or one direct loan category; she can, however, still form a portfolio of direct loans by investing in different categories across multiple days.[22] A direct lender chooses to invest in a given loan category based on the utility she derives from its characteristics. The indirect utility of lender i investing in loan

[22]This modeling assumption is justified by the data, as conditional on investing the median number of loan categories or portfolio products in which a lender invests on a given day is 1. It is also motivated by the potential search costs that lenders face when searching through a large number of loans available on the platform.

category c on day t is:

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

where r_{ct} denotes the loan category's yield, m_{ct} its maturity, a_{ct} its amount, and z_{ct} are other characteristics of the loan category observable to the lender (all variables in Panel A of Table 3, plus *time to first investment* and *time from first to last investment* from Table 1). 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 $\delta_{ict}^{D} = \gamma_{it}' x_{ct} + \zeta_{ct}$. The variables *time to first investment* and *time from first to last investment* respectively measure the time between the instant the loan is posted on the platform and the moment it receives the first investment, and the time between the first and last investment the loan obtains. These variables capture a "peer-effect" component of loan attractiveness, as an individual investor can perceive shorter investment times in a loan category as a signal that the platform and other investors consider it as valuable. We do not explicitly model lenders' sensitivity to a single variable capturing borrower's default risk, but rather assume that the borrower and loan characteristics included in equation (1) are used by lenders to predict risk.

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. As a proxy for liquidity risk-tolerance, as discussed we use a measure of the lenders' activity on the platform.

Each lender can also invest in a portfolio product $k = 1, \ldots, K_t$ among those available on a given day t. As remarked, only very rarely we observe lenders funding portfolio products and direct loans simultaneously; we thus treat these two options as mutually exclusive.[23] The indirect

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

utility of lender i choosing portfolio product k on day t is:

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

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. $\mathcal{L}_{kt}$ denotes the portfolio product's liquidity, defined as the time it takes for its underlying loans to be resold on the secondary market at maturity, or resale time.[24] We assume that lenders have rational expectations of each portfolio's resale time.[25] 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 $\delta_{ikt}^{P} = \alpha_{it}' \mathcal{X}_{kt} + \xi_{kt}$.

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

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

where ν_{jkt} is a normally distributed shock.

Finally, lenders have the outside option of investing outside the platform or not investing at all. Ideally, we would like to capture what part of the population of potential lenders (market size)

[24] As specified in equation (1), we assume that lenders investing in direct loans do not consider loan liquidity in their decision. This is motivated by three reasons. First, while portfolios always have a positive resale time at maturity that we can easily measure, direct loans have zero resale time at maturity. Second, if investors liquidate a loan before it reaches maturity, resale time would change depending on when the loan is sold, making it infeasible to measure resale time accurately. Third, most of the marketplace credit portfolios are liquidated at maturity (the rollover rate is around 12% on average), when the underlying loans need not have reached maturity yet; in contrast, the vast majority of direct loans are held until maturity.

[25] We treat $\mathcal{L}_{kt}$ as an exogenous portfolio attribute. We discuss this choice in Section 6.C, where we argue that our conclusions are not sensitive to it.

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

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

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

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

B Platform

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

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

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

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

where:

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

and υ_{kct} are normally distributed demand shocks at the portfolio–loan category–day level unobserved by the econometrician. This functional form and approach are similar in spirit to Koijen and Yogo (2019).[26] 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^r_{kt} captures the platform's preference in the risk-return tradeoff between earning a greater profit margin $r_{ct} - \mathcal{R}_{kt}$ and selecting loans from

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

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.[27] For these reasons, we focus our analysis, and the platform's optimization problem discussed below, on these two parameters.[28]

We also assume that the platform predicts the average default rate d_{ct} for each loan category c on each day t, based on past defaults for that category up to day t. This is motivated by the fact that the platform has access to the performance record of all loans. In contrast, individual lenders can have access only to partial information on past performance, and likely face higher costs of collecting and processing those data. Moreover, the borrower and loan characteristics that lenders observe represent the information they use to assess the loans' default risk. This preference for the average default rate of a loan category represents the channel through which the platform internalizes investors' aversion to default risk in its portfolio choice.

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:

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

where $\mathcal{T}_t \mathcal{S}_{kt}^{P}$ 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

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

[28] The creation of portfolios by the platform has points of contact with securitization, as the performance of each portfolio depends on the underlying pool of loans and the same loan can in principle enter multiple portfolios (the median loan enters 5 portfolio products on Renrendai). It differs from securitization, on the other hand, because loan pools are not divided up into tranches of different seniority like in mortgage-backed securities and collateralized loan obligations: a default on loan *x* affects the performance of all portfolios invested in loan *x* at the same time. Moreover, the platform does not retain the riskier/equity-like tranches.

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.[29] 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 borrowers' fees, which characterizes portfolio k and does not vary across loan categories.[30]

We model $\mathcal{C}_{1kct}$ as $\beta^m_{kt} m_{ct} \overline{\mathcal{C}}_{1kt}$, where β^m_{kt} denotes the platform's maturity mismatch parameter from equation (6), and $\overline{\mathcal{C}}_{1kt}$ is a scalar unobserved by the econometrician, but which can be recovered using the first-order conditions of the profit function as illustrated in Appendix C. The marginal cost $\mathcal{C}_{1kct}$ 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). $\mathcal{C}_{1kct}$ is also an increasing function of the maturity mismatch parameter β^m_{kt}, reflecting the fact that when the maturity mismatch is greater, the platform bears a higher cost of screening and monitoring on loans that represent a larger fraction of its portfolio. Equation (7) does not include a cost related to liquidity risk, because under the marketplace paradigm the platform does not bear liquidity risk, which is entirely borne by investors. In Section 6, we discuss a counterfactual bank-like paradigm, where the platform bears liquidity risk; in that setting, the profit function includes a liquidity risk term.

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 $\mathcal{R}_{kt}$

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

[30]The cost component $\mathcal{C}_{1kct}$ can also be interpreted as capturing the loss from a loan category's default risk, as most loans are guaranteed by the platform. We choose not to introduce more explicitly loans' default risk in the platform's profit function because of the very low incidence of default for loans financed via portfolio products (0.04%). Regarding $\mathcal{C}_{2kt}$, borrower fees are not reported in our data. However, they are identical whether a loan is funded via direct lending or as part of a marketplace loan portfolio. Therefore, they are neutral to the platform's choice.

and preference for underlying loan maturity β_{kt}^m for each portfolio product.[31] The platform solves:

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

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 equation (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.

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 $\mathcal{L}_{kt}$ captures this feature of the secondary market for each portfolio k at its maturity.

The demand for loans is defined, as in the primary market, by the direct lenders' market share equation (4) and the platform's portfolio weights (5). For each portfolio product k on day t, demand

[31] We solve the platform's optimization problem as a function of the maturity preference parameter β_{kt}^m rather than portfolio product maturity for tractability. There are only a handful of portfolio maturity options available on the platform (3, 6, 12, 18, and 24 months), whereas focusing on β_{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.

equals supply in equilibrium. The supply of portfolio products is determined by the platform maximization problem (8), and the demand by their market shares $\mathcal{S}_{kt}^{P}$.

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 chooses a given loan category from equation (4), and analogously for portfolio products. To account for lender preference heterogeneity, as discussed we use activity on Renrendai as an index of lender sophistication and liquidity risk-tolerance. Intuitively, only lenders with deeper pockets, who have greater capacity to bear liquidity risk, can incur the minimum investment cost frequently. To aggregate this measure across all lenders in equation (4), we focus on the percentage of active lenders (in the top 5% of the active investing distribution in a given calendar quarter) among all investors who operate on the platform on a given day t; we 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. In other words, we recover the average preferences for heterogeneous lenders, ranging between active and inactive ones.

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

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

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

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

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

where $\mathcal{R}$ denotes the portfolio's target return, $\mathcal{M}$ its maturity, $\mathcal{A}$ the target size of the portfolio, and $\mathcal{Z}$ collects other observable attributes of the portfolio. We also include liquidity risk $\mathcal{L}_{kt}$ (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 write equations (9) and (10) separately for expositional convenience, but they are actually part of a single demand system that combines lender choices to invest in direct loans and portfolio products, and allows for direct substitutability between the two channels. The two equations are hence jointly estimated as part of one regression model.[32]

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

[32] Alternative approaches could be a mixed logit model (Train 2009) or the random coefficients logit demand model of Berry, Levinsohn and Pakes (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.

investors, which we denote with $\mathcal{S}_{kt}^{Roll}$:

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

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

Finally, we estimate the platform's demand for loans in a similar fashion as for equations (9) and (10), but with the difference that 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 normalize all δ_{kct} with respect to one of the alternatives within portfolio k issued on day t. This leads to the following specification:

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

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

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 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, is unrealistic: as discussed, 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.

Even though the platform's institutional setting mitigates these potential identification concerns, we also provide for robustness a set of results using instrumental variables for portfolio returns and loans' interest rates in the lenders' demand model. We use as instruments the heterogeneous pass-through of monetary policy, the Shibor index, across portfolio products and loan categories, in the spirit of Villas-Boas (2007) and Egan et al. (2017). The intuition is that the cost of credit for borrowers at traditional intermediaries increases when the Shibor rises, which in turn positively impacts the interest rate that borrowers post on the platform when requesting a loan, as well as the return that the platform offers on its portfolios. This pass-through is heterogeneous across portfolio products and loan categories due to their different maturity structures, and due to the different preferences for maturity that borrowers and lenders have. By including day fixed effects we control for the direct effect of changes in Shibor on lenders' demand for loans and portfolios, allowing the Shibor to only impact their demand via changes in portfolio returns and loan categories' interest rates.

5 Results

In this section we present the estimates of the models from Section 4. Table 4 describes the lenders' demand for direct loans and portfolio products, both for the OLS (columns 1 and 3) and IV (columns 2 and 4) estimates. As we find that almost all OLS and IV coefficients are not statistically different from each other, we focus on the OLS estimates, but we provide counterfactual results using both the OLS and IV estimates. 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% (83 bps) higher target return increases the demand for a given loan category by 4.6% on average; in comparison, a 10% higher 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 to liquidity risk; however, active investors are less averse. The corresponding demand elasticity is reported in Table 5; on average, a 10% increase in resale time $\mathcal{L}$ (about 1.3 hours) reduces portfolio product demand by about 0.03%. However, that same 10% increase in resale time reduces demand from less active lenders (10^{th} percentile) by about 0.06%, while it reduces demand from more active lenders (90^{th} percentile) by just 0.001%. Average resale times below one day do not have a big impact on investors' demands. In the counterfactuals discussed in Section 6, we consider a "stress test" scenario with resale time of 30 days, and study its impact on demand, credit amounts, and platform profits.

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.[33]

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 re-

[33]In principle, the yields offered by the borrowers when they apply for a loan could be endogenous to expected demand. We discussed in Section 3 several arguments why this is unlikely an issue, as the borrowers are unlikely sophisticated and the characteristics of the borrower population do not appear to change over time. In addition, in additional tests omitted for brevity we estimate the models of Table 4 using two-stage least squares, where the promised returns on direct loans and marketplace portfolios are instrumented using the Berry et al. (1995) instruments as well as characteristics of the borrower's location. The estimates of the coefficients on loan and portfolio returns are similar to the ones reported in Table 4.

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

	Direct loan		Portfolio product	
	OLS	**IV**	**OLS**	**IV**
Log Return ($\mathcal{R}_{kt}$, r_{ct})	0.30	0.16	0.23	0.26
	(0.08)	(0.08)	(0.13)	(0.16)
Log Return ($\mathcal{R}_{kt}$, r_{ct}) $\times$ Active lenders %	2.94	2.20	2.31	2.43
	(1.12)	(1.16)	(1.11)	(1.87)
Log Maturity ($\mathcal{M}_{kt}$, m_{ct})	0.27	0.29	0.01	–0.01
	(0.02)	(0.02)	(0.03)	(0.04)
Log Maturity ($\mathcal{M}_{kt}$, m_{ct}) $\times$ Active lenders %	0.22	0.15	–0.59	–0.50
	(0.23)	(0.25)	(0.25)	(0.28)
Log Amount ($\mathcal{A}_{kt}$, a_{ct})	0.52	0.52	0.99	0.98
	(0.01)	(0.01)	(0.03)	(0.03)
Log Amount ($\mathcal{A}_{kt}$, a_{ct}) $\times$ Active lenders %	0.11	0.13	0.24	0.53
	(0.17)	(0.18)	(0.27)	(0.37)
Resale Time ($\mathcal{L}_{kt}$)			–5.41	–5.78
			(2.08)	(2.32)
Resale Time ($\mathcal{L}_{kt}$) $\times$ Active lenders %			53.72	59.23
			(32.22)	(36.79)
Channel f.e.	0.85	0.28	1.87	1.87
	(0.38)	(0.40)	(0.05)	(0.05)
Portfolio product controls	Yes			
Loan category controls	Yes			
Day f.e.	Yes			
N. obs.	89,157			
Adj. R^2 (OLS estimates)	0.734			
Kleibergen-Paap F Statistic (IV estimates)	64.39			

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 first and third columns report the OLS estimates, the second and fourth columns the corresponding IV estimates. The standard errors, reported in parentheses, are clustered around interactions of days, channel, and promotional portfolio products, for a total of 3,697 clusters.

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	0.4562	0.0572	0.3962	0.4478	0.5274
Portfolio Return	718	0.3173	0.0715	0.2621	0.3190	0.3934
Portfolio Resale Time	718	–0.0027	0.0084	–0.0064	–0.0007	–0.0001

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

turns and longer maturities. We interpret these results as suggesting that the platform uses both the interest rates and maturities set by the borrowers to alleviate adverse selection problems. Riskier borrowers offer high interest rates and shorter maturities as they may struggle to obtain funding otherwise. In the spirit of Stiglitz and Weiss (1981), by forming portfolios with loans offering lower interest rates and longer maturities, the platform obtains lower returns on the average loan but extends credit to a pool of safer borrowers.[34] Interestingly, that contrasts with the behavior of direct lenders, who, as we discussed, favor higher returns.[35] This interpretation is corroborated by the results in Table 6, which show that the platform avoids loan categories with higher default rates.[36] 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

[34] Hertzberg, Liberman and Paravisini (2018), using data from the U.S. marketplace lending platform LendingClub, find that riskier borrowers self-select into longer maturities. That is due to the fact that LendingClub 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.

[35] Our interpretation of these 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.

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

TABLE 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.

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.[37] This is in line with the descriptive evidence of Section 2, suggesting that the platform has little ability to affect the secondary market for the loan (we return to this point in Section 6.C).

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

TABLE 7—ROLLOVER RATE OF PORTFOLIO PRODUCTS

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 ($\mathcal{L}_{kt}$)	–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.

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 lenders can only choose between peer-to-peer credit and the outside option. That allows us to quantify the welfare value of intermediation by the platform. Second, we simulate a "bank-like" scenario where the platform sells loan portfolio products as under the marketplace model, but bears liquidity risk like a traditional bank. That allows us to study the impact of the maturity mismatch between portfolio products and their underlying loans. We simulate two versions of this counterfactual, under baseline (i.e., relatively high) liquidity and under low liquidity. Third, we replicate the bank-like counterfactual, changing the composition of the lender population by reducing the incidence of active lenders. That allows us to understand which lenders benefit the most from marketplace credit and which from bank-like credit.

In the 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 $\mathcal{L}$ is removed from the lenders' indirect utility and rollover decision equations. Second, the profit on a given portfolio product k is now written as:

$$\Pi_{kt} = \mathcal{S}^{P}_{kt}\mathcal{T}_t \Bigg\{ \underbrace{\sum_{c \in m \leq \mathcal{M}} w_{kct}\left(r_{ct} - \mathcal{C}_{1kct}\right) m_{ct}}_{\substack{\text{Not exposed to} \\ \text{liquidity risk}}} + \underbrace{\sum_{c \in m > \mathcal{M}} w_{kct}\left(r_{ct} - \mathcal{C}_{1kct}\right)\left[m_{ct} - \left(1 - \mathcal{S}^{Roll}_{kt}\right)\frac{m_{ct}}{\mathcal{M}_{kt}}\mathcal{L}_{ct}\right]}_{\substack{\text{Exposed to} \\ \text{liquidity risk}}} - \mathcal{R}_{kt}\mathcal{M}_{kt} - \mathcal{C}_{2kt} \Bigg\}. \tag{13}$$

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

The second revenue term denotes loans with maturity $m > \mathcal{M}$, i.e., longer than the portfolio maturity $\mathcal{M}$. In this case the platform is exposed to liquidity risk, and will have to refinance the underlying loans when the portfolio product reaches its maturity. A loan can be refinanced in two ways. First, the original lender may roll her portfolio investment over; that happens with probability $\mathcal{S}^{Roll}_{kt}$ 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 $1 - \mathcal{S}^{Roll}_{kt}$. In that case, the underlying loans are moved to the secondary market, where they can be bought by a direct lender or (more frequently) they can be taken up to become part of a new marketplace loan portfolio; either way, a resale time elapses, which comes with a loss of revenue for the platform. 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. While in the baseline scenario the platform was neutral with respect to liquidity risk, since it did not bear it, in the counterfactual it becomes averse to liquidity risk through the revenue loss. 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) captures 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 $\mathcal{S}^{P}_{kt}$ is increasing in the target return, and so is the rollover probability $\mathcal{S}^{Roll}_{kt}$, 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.[38]

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.[39]

In the first place, restricting credit to direct (peer-to-peer) lending induces a welfare loss. In Table 8 we show that it is associated with a 65% drop in credit provision and a 55% lower lender surplus in comparison to the baseline case.[40] That highlights the substantial benefits of platform intermediation through portfolio products, and provides a rationale for the transition to the mar-

[38] We 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.

[39] In Appendix Tables D.3 and D.4 we report the same counterfactual results, but based on the IV estimates of Table 4 instead of the OLS ones. Results are qualitatively and quantitatively very similar.

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

ketplace model. The drop in lender surplus and credit provision can be due to three, non–mutually exclusive factors: (a) a search cost advantage, if the platform is able to locate loans in which to invest faster than peer-to-peer lenders, (b) an information advantage, if the platform is better able to screen and/or monitor borrowers, or (c) the bigger choice set under the marketplace model for the lenders, as portfolio products can have a shorter maturity than the underlying loans.[41]

The median time until the first investment is 245 minutes for loans funded by peer-to-peer investors and 307 minutes for loans that become part of portfolio products, suggesting that search costs are not economically very different between peer-to-peer investors and the platform. To determine the impact of the platform's information, we simulate an additional counterfactual, in which we remove the default rate d_{ct} from the determinants of the platform's portfolio weights in equation (6), so that the peer-to-peer lenders and the platform have access to identical information. The results, reported in Appendix Table D.2, are qualitatively and quantitatively very close to the ones in Table 8. This suggests that the platform's information is also not the main driver of the difference in lender surplus and credit provision between the marketplace and peer-to-peer models. This is perhaps not surprising: the platform can only invest in loans to borrowers with credit rating AA or higher, which are less subject to adverse selection problems. The main driver appears to be the fact that maturity mismatch allows the platform to offer a greater assortment of portfolios to the lenders, who are not constrained to invest in loans matching their investment horizon. This is consistent with the evidence of Table 4, which shows that lenders investing in portfolio products prefer shorter maturities; and indeed, over 90% of the portfolio product investment is done under maturity mismatch.

Table 8 also shows that under base liquidity and base active lenders bank-like credit has very similar outcomes relative to marketplace credit. Credit provision levels are almost identical and lender surplus increases by 0.2% in relative terms. The platform's profits are only 0.17% lower than under the marketplace model.

[41]To distinguish it from screening and monitoring, we define search here in a narrow sense, as the opportunity cost of the time spent on the platform's website searching for loans in which to invest. Given that the platform only invests in AA rated loans for its portfolio products, that have on average a default rate of just 0.04%, risk diversification via portfolio products likely plays a very limited role.

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.

The differences between the marketplace and bank-like models become more visible in Table 9, where we examine the impact of liquidity risk and lender population composition. In all the scenarios simulated in Table 9, we assume a longer resale time than in the baseline scenarios of Table 8, i.e., higher liquidity risk, increasing $\mathcal{L}$ to 30 days. Although much longer than the baseline average resale time 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.[42] 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 maturity mismatch, however, adjusts very little. That makes intuitive sense, given that the distribu-

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

tion 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.[43]

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 carries through with a lower than 30 days resale time if we further increase the proportion of inactive lenders on the platform. Our model 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).

Taken together, these results are consistent with a narrative in which, in the early days of online debt crowdfunding, the sector mainly attracts risk-tolerant lenders, who seek higher returns and have higher welfare under the peer-to-peer and marketplace models. As the clientele of lenders

[43] As described in Section 2, we observe very low default rates of funded borrowers, and these remain very low also across different scenarios and platform models, hence we do not report them here.

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

Active lenders share:	Base		Low	
Outcome	**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.

grows, it comes to encompass more risk-averse investors, who are more sensitive to liquidity risk and have higher welfare under the bank-like model. Moreover, our findings are in line with anecdotal evidence about the most developed platforms such as LendingClub, Funding Circle, Zopa, or RateSetter, which have shut down peer-to-peer credit, while offering securitized (marketplace) loan portfolios to a more risk-tolerant institutional investor clientele as well as, more recently, traditional banking products to more risk-averse retail investors.[44]

C Discussion on resale time

In our model, the platform determines the lenders' exposure to liquidity risk/resale time by choosing the degree of maturity mismatch, β^m_{kt}, in each portfolio product. Moreover, by choosing portfolio returns, it can steer investors towards portfolios with more or less maturity mismatch, and also affect their rollover decision, again influencing exposure to liquidity risk. Beyond this, we do not explicitly model the mechanism that determines resale time $\mathcal{L}$, 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. 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

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

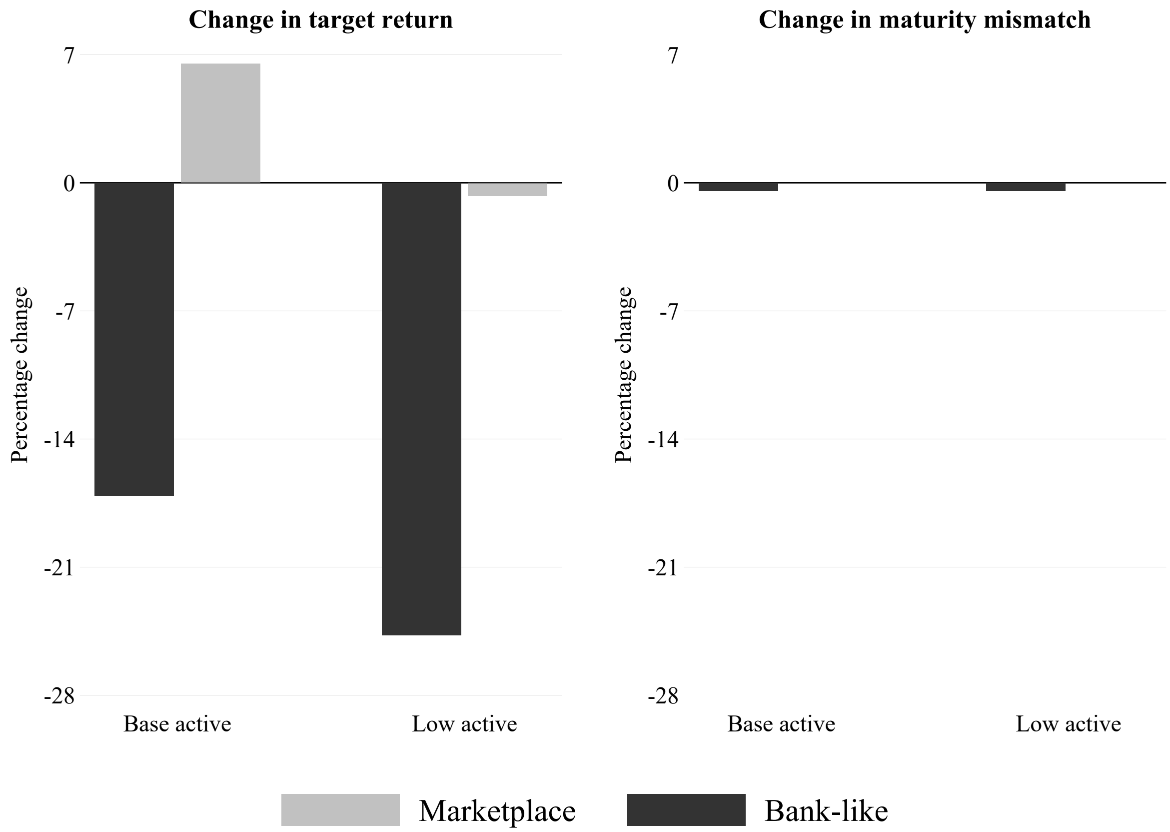

FIGURE 3. LOW LIQUIDITY: AVERAGE CHANGE IN RETURN AND MATURITY MISMATCH

Notes: The plot on the left illustrates the percentage change in portfolio product target returns following an increase in resale time to 30 days, under the marketplace credit (darker-shader bars) and bank-like credit (lighter-shaded bars) models, assuming that the population has a baseline fraction of active investors (i.e., the same as in the counterfactuals of Table 8) or a low fraction of active investors (i.e., a 30% reduction in the fraction of active lenders). The plot on the right illustrates the percentages change in portfolio product maturity mismatch. In both plots, the percentage changes are expressed relative to a baseline scenario that assumes marketplace credit, time to resale equal to one-half of one day, and the baseline fraction of active investors (i.e., relative to the conditions corresponding to the first column of Table 8).

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.[45]

[45]In additional tests, omitted for brevity, we also conduct a covariance analysis (ANCOVA) to decompose the variation in resale time attributable to macroeconomic variables (outside the control of the platform) and conditions offered by the platform. We aggregate each loan transaction's resale time at the monthly level, and regress it on the CSI 300 index return, the Shanghai interbank 1-year offered rate, and quarterly GDP (both contemporaneous and lagged 6 months). To capture elements under the control of the platform, we also include the total number of lenders, total number of loans, and the average daily search times of Renrendai on Baidu, the main Chinese search engine. This specification generates an R-squared of 0.82. Crucially, the conditions that are arguably more under the control of Renrendai (number of lenders, number of loans, and the average daily search times) contribute to only 3% of the

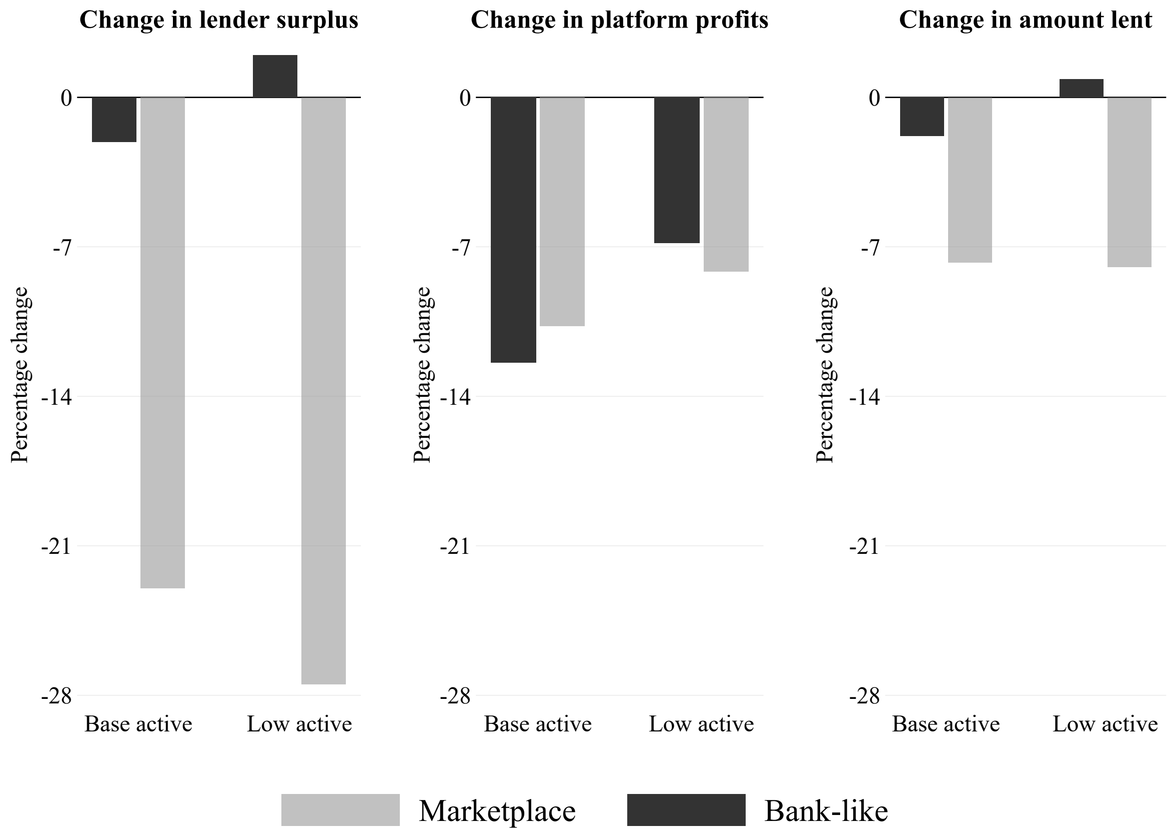

FIGURE 4. LOW LIQUIDITY: AVERAGE CHANGE IN LENDER SURPLUS, PLATFORM PROFIT, AND AMOUNT LENT

Notes: The plot on the left illustrates the percentage change in lender surplus following an increase in resale time to 30 days, under the marketplace credit (darker-shader bars) and bank-like credit (lighter-shaded bars) models, assuming that the population has a baseline fraction of active investors (i.e., the same as in the counterfactuals of Table 8) or a low fraction of active investors (i.e., a 30% reduction in the fraction of active lenders). The plot in the middle illustrates the percentages change in platform profits. The plot on the right illustrates the percentage change in amount lent. In all plots, the percentage changes are expressed relative to a baseline scenario that assumes marketplace credit, time to resale equal to one-half of one day, and the baseline fraction of active investors (i.e., relative to the conditions corresponding to the first column of Table 8).

Second, endogenizing resale time is unlikely to deliver additional economic insight. 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 $\mathcal{L}$, 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 $\mathcal{L}$, because the lenders do not bear the cost of a longer resale time. Under the marketplace model

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

an increase in lender liquidity risk-aversion creates an incentive for the platform to reduce $\mathcal{L}$, as it affects lender demands and, through them, platform profits.[46] 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 of our counterfactuals.

Third, 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 and introducing complex dynamic considerations. 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. Based on these arguments, and following the literature on characteristics-based asset demand models (Koijen and Yogo 2019), we focus mainly on portfolio returns and maturity mismatch as endogenous variables in our model.

7 Conclusion

We develop and estimate an equilibrium model of online debt crowdfunding as a laboratory to study the value of financial intermediation. We exploit the fact that under different online lending paradigms the crowdfunding platform plays different roles: under the peer-to-peer paradigm it merely provides a trading venue to lenders and borrowers; under the marketplace credit paradigm it sells to investors loan portfolios that exhibit maturity mismatch, but bears no liquidity risk; and more recently under the bank-like paradigm if offers to retail investors products that resemble traditional bank deposits. Our empirical setting attenuates the potential confounding effects of regulation, since online credit was very lightly regulated in China during our sample period, and of

[46]Rather than reducing $\mathcal{L}$, 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.

the complexity of the business of traditional intermediaries, since online lending platforms focus exclusively on intermediating credit in our sample.

We estimate our model using the universe of loans and loan applications on Renrendai, a leading Chinese marketplace credit platform. Our approach recovers lender preferences from observed investment choices, and allows us to simulate counterfactuals to contrast marketplace credit to the 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 is low, but the bank-like model is welfare-increasing when liquidity is low and lender liquidity-risk aversion is 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 intermediaries increasingly compete with traditional players.

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Online Appendix

A Variable definitions

<u>LOAN APPLICATIONS</u>

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

<u>FUNDED LOANS</u>

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

Maturity Maturity of the loan expressed in months

Number of lenders Number of lenders financing the loan

Open to 1st investment (minutes) 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

<u>PORTFOLIO PRODUCTS</u>

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

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

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

Minimum Investment Minimum investment necessary to acquire a portfolio product

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

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

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

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

<u>BORROWERS</u>

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.

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

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

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

<u>LENDERS</u>

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:

$$\frac{\partial \Pi_t}{\partial \beta^m_{kt}} = \mathcal{S}^P_{kt}\mathcal{T}_t\left[\sum_c \frac{\partial w_{kct}}{\partial \beta^m_{kt}}\left(r_{ct} - \beta^m_{kt} m_{ct} \overline{\mathcal{C}}_{1kt}\right) m_{ct} - \sum_c w_{kct} m_{ct} \overline{\mathcal{C}}_{1kt} m_{ct}\right] = 0$$

So that the condition is:

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

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

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

This may be rewritten as:

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

Thus the condition is:

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

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:

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

So that the condition is:

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

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 observcation 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 positon, 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.

TABLE D.2—ADDITIONAL COUNTERFACTUAL: MARKETPLACE MODEL WHEN THE PLATFORM HAS NO INFORMATION ADVANTAGE

Outcome	**Marketplace**
Average return (%)	8.10
Average maturity mismatch (months)	22.30
Amount lent (bn ¥)	19.90
Amount lent Plan (bn ¥)	16.55
Average change lenders' surplus (%)	–0.04
Average change platform profit (%)	–0.20

Notes: The table summarizes the results of a counterfactual similar to the one reported in Table 8, column (1), but where the average default rate d_{ct} is removed from the platform's indirect utility (6). All other inputs are identical to Table 8, column (1). Removing the average default rate d_{ct} results in the platform having identical information as peer-to-peer lenders; this counterfactual can thus be interpreted as isolating the effect of the greater choice set provided to the lenders under the marketplace model as opposed to the peer-to-peer model.

TABLE D.3—COUNTERFACTUALS BASED ON IV ESTIMATES – 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	0.12	–18.04
Average change platform profit (%)	0.00	–0.20	

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.

TABLE D.4—COUNTERFACTUALS BASED ON IV ESTIMATES – LOW LIQUIDITY: MARKETPLACE AND BANK-LIKE, BASE AND LOW ACTIVE LENDERS

Active lenders share:	**Base**		**Low**	
Outcome	**Market-place**	**Bank-like**	**Market-place**	**Bank-like**
Average return (%)	8.62	6.91	8.07	6.31
Average maturity mismatch (months)	22.30	22.20	22.30	22.20
Amount lent (bn ¥)	18.34	19.42	18.10	19.82
Amount lent Uplan (bn ¥)	15.37	16.02	15.04	16.18
Average change lenders' surplus (%)	–18.54	-1.00	–35.42	-8.60
Average change platform profit (%)	–9.32	–11.43	–9.07	–7.32

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

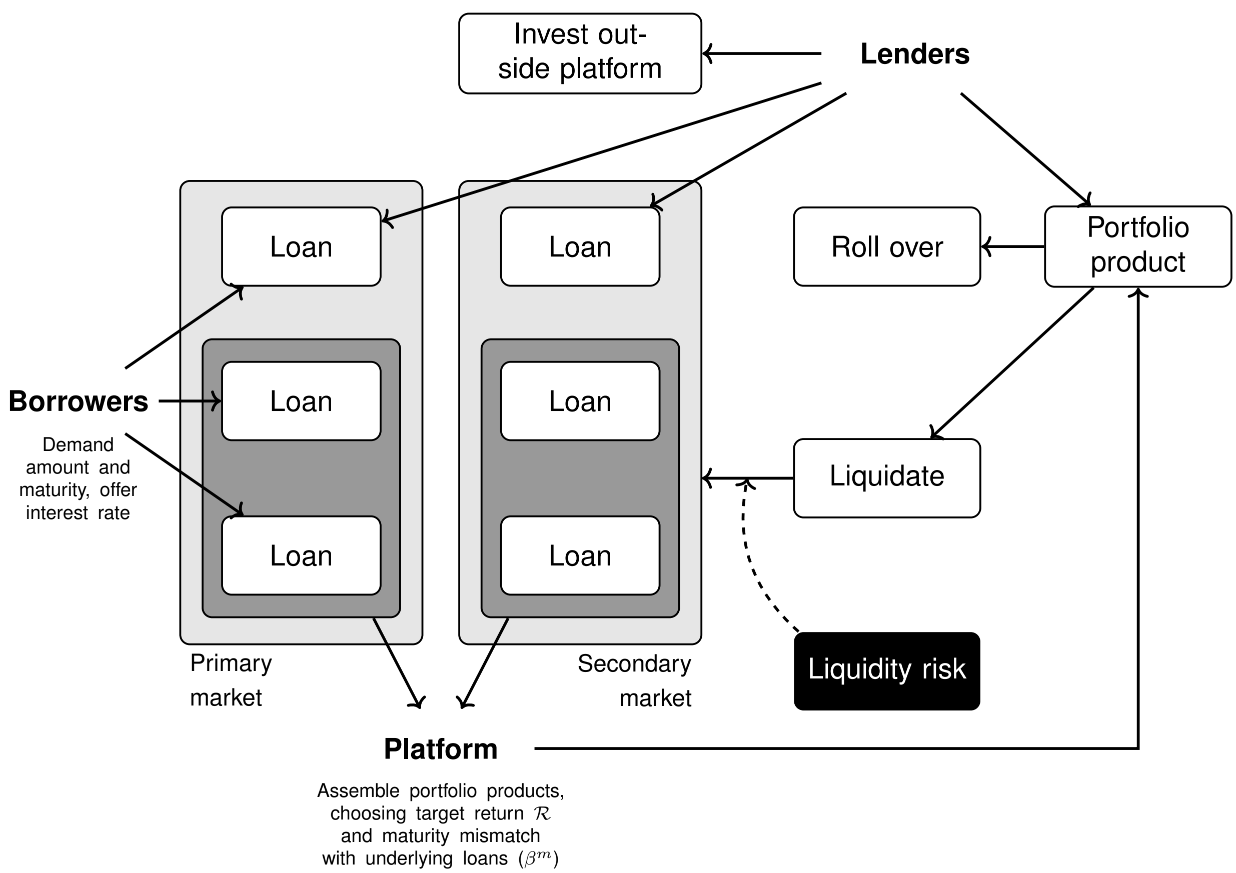
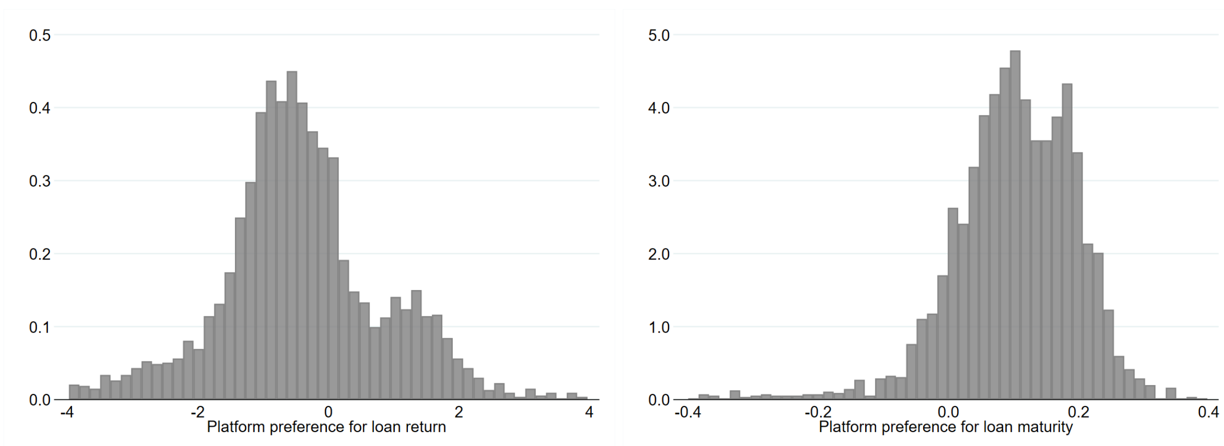


FIGURE D.2. PLATFORM PREFERENCES FOR LOAN RETURN AND MATURITY



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