Is FinTech a Threat to Financial Stability?

Evidence from Peer-to-Peer Lending in China

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Abstract

We study the impact of P2P lending on household leverage. We rely on a novel, hand-collected database, including detailed information on all lending transactions at Renrendai, a leading Chinese peer-to-peer (P2P) lending company. We exploit a policy intervention in the market for real estate mortgages in a number of major Chinese cities, which increases the demand for P2P lending, leaving overall credit demand unchanged. We analyze P2P loan applications and credit outcomes around the policy intervention, comparing affected and un-affected cities in a difference-in-differences setting. Our test provides comparatively clean empirical evidence on the capacity of P2P lending to lead to excessive levels of household debt and undermine policy interventions in the credit market. More broadly, it can inform the ongoing debate on FinTech and the regulatory challenges posed by the disintermediation of financial services.

JEL codes: G23; G01; G18.

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The global financial meltdown of 2007-2009 brought household leverage to the forefront of the academic and policy debate. Evidence of its role as a driver of the U.S. mortgage crisis (Adelino, Schoar, and Severino (2012, 2016), Mian and Sufi (2009, 2011), Mian, Sufi, and Trebbi (2015)), that financial crises are often preceded by rapid credit growth (Bordo (2008), Claessens, Kose, and Terrones (2012), Schularick and Taylor (2012)), and that expansions of the credit supply can generate disruptions in the real economy (Mian and Sufi (2010), Di Maggio and Kermani (2017)) has prompted policy efforts in many countries to contain household leverage and prevent the buildup of asset price bubbles, particularly in the real estate sector (Jácome and Mitra (2015)).

Such policies typically target traditional financial intermediaries such as banks, mostly by enforcing loan-to-value restrictions via minimum down-payment requirements (Claessens (2015)). This focus, however, might be too narrow if households have access to alternative, unregulated credit channels that allow them either to increase leverage directly or to circumvent limits on borrowing from regulated intermediaries. In this paper, we assess the empirical relevance of one such alternative channel: Peer-to-peer (P2P) lending.

By now rivaling traditional credit providers in size and reach (Morse (2015)), P2P lending has experienced double-digit growth in developed economies such as the U.S. (where loan volumes amounted to $77bn in 2015), the U.K. ($471m, Atz and Bholat (2016)), and continental Europe ($616m, Masane-Ose (2016)). [1] The fastest-growing P2P lending market, however, is China, which is also estimated to be the largest in the world (Deer, Mi, and Yuxin (2015)), with loan volumes totaling over $90bn (RMB 600bn) as of June 2016 and corresponding to about 20% of consumption loans to households provided by traditional banks.[2]

[1] E. Robinson, “As money pours into peer-to-peer lending, some see bubble brewing”, *Bloomberg*, May 15, 2015.
[2] G. Wildau, “Chinese P2P lending regulations target hucksters and risk-takers”, *Financial Times*, August 24, 2016.

P2P lending companies provide websites where borrowers can solicit funds from investors. There is a large assortment of business models, but mostly the company acts as a "broker," offering an online platform that brings together borrowers seeking funding and prospective investors willing to lend cash. By matching borrowers and lenders directly, P2P companies bypass the role traditionally played by banks, disintermediating credit.

Disintermediation has pros and cons. On the one hand, the absence of an intermediary can allow P2P borrowers and lenders to capture some of the rents typically appropriated by banks (Morse (2015)). Moreover, by relying on different forms of information and/or using "social" information more effectively, P2P lending can relax credit constraints and finance borrowers who are cut off from traditional bank lending (Balyuk (2017), Freedman and Jin (2014), Lin, Prabhala, and Viswanathan (2013), Morse (2015)).

On the other hand, because P2P lending is not subject to the same scrutiny that traditional banks receive from financial markets and regulators, it may pose new risks to the financial system, for instance by helping circumvent regulatory credit supply restrictions. This has raised concerns that P2P lending can lead to an excessive build-up of household leverage, suggesting parallels with the U.S. mortgage crisis.[3] Our objective is to determine the capacity of P2P lending to fuel household debt creation, and to assess to what extent P2P lending can interfere with regulatory action in credit markets.

Taking these questions to the data confronts us with two empirical challenges. First, we are interested in gauging the capacity of P2P credit supply, but the equilibrium in the market for loans also depends on credit demand, and separating demand and supply is difficult, because the econometrician typically only observes lending outcomes ex post.[4] One approach to identify supply is to trace it out with

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[3] P. Jenkins, "US peer-to-peer lending model has parallel with subprime crisis", *Financial Times*, May 30, 2016.
[4] This problem is partly attenuated in our data, because we can observe all loan applications, including ones that do not eventually result in a loan.

demand shifts (Koopmans (1949)). This, however, requires a shock to the demand for P2P lending, which does not separately affect its supply.

Second, in order to trace out credit supply with demand shocks, we must control for potential supply-side drivers, mainly in the form of unobserved heterogeneity among P2P lenders. For instance, lenders may differ in terms of their proximate knowledge, due to their expertise (Morse (2015)), or their ability to harness information from social circles for screening and monitoring (Freedman and Jin (2014), Lin, Prabhala, and Viswanathan (2013)). To the extent that lenders' characteristics such as these can vary with the exposure of their borrowers to a demand shock, the resulting simultaneous changes in lending demand and supply can confound the interpretation of a test. Thus, while we study the effects of a change in P2P lending demand, we want to be able to hold P2P the lending supply curve fixed.

In sum: To design a test, we need a shock to the demand for P2P lending, as well as a way to hold P2P lending supply fixed. The setting of our test allows us to address the first challenge. The structure of our data helps us address the second one, with a fixed effects strategy.

We study P2P lending around a regulatory change in the Chinese real estate market, which takes place in 2013. The city governments of a number of large Chinese cities impose a 16.7% increase in the minimum down-payment required to obtain a mortgage for the purchase of a second home, from 60% to 70% of the property's value. The objective is to slow down the growth in real estate prices by limiting credit, following a policy impulse in this direction by the Chinese central government.[5] Anecdotal evidence, however, suggests that real estate investors circumvent the new requirements, borrowing via P2P lending platforms to reach the increased down-payment.[6] In other words, with a relatively small

[5] "Shanghai Raises Home Down-Payment Requirement as Prices Jump", *Bloomberg*, November 8, 2013, and "China's Nanjing, Hangzhou Raise 2nd Home Down Payments", *Bloomberg*, November 27, 2013.
[6] D. Weinland, and Y.Yang, "China to Crack Down on P2P Lenders," *Financial Times*, March 14, 2016.

contribution from the P2P platforms, households can still increase their leverage. Even more importantly, the regulatory change creates a positive shock to P2P lending demand.[7]

We exploit the change in down-payment requirements in a difference-in-differences setting, studying changes in P2P lending around this episode, for affected and un-affected cities. To analyze the impact of the changes in mortgage down-payment requirements on P2P credit, we assemble a novel, hand-collected database containing *all* P2P loan applications and lending outcomes from a leading Chinese P2P lending company, Renrendai (人人贷). Importantly, our database provides all the lending transactions executed within the platform and it matches each borrower with her lenders. As a result, we are able to exploit its depth, and study the impact of shocks to P2P lending demand while holding lending supply constant, using a fixed effects strategy.

Our results are consistent with P2P lending providing a disintermediated and unregulated source of credit, with the potential to undermine policy interventions in credit markets. In the analysis, we are very careful about identification and what we can and cannot conclude from our results; our main effects, however, are already visible in Figure 1, which plots loan applications volumes at Renrendai, for "treatment" cities as well as "control" cities, around the 2013 increase in minimum down-payment requirements. Prior to the last quarter of 2013, P2P loans in treated and control cities exhibit parallel trends: they overlap over the entire two-year period preceding the regulation change. Following the last quarter of 2013, loans in the treated cities increase sharply, consistent with an influx of applications to help meet the higher down-payments. While Renrendai loan applications grow in both groups, due to the development of P2P lending in China during our sample period, applications at the treated cities grow

[7] The cities imposing the increase in down-payment requirements are Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenyang, Shenzhen, and Wuhan. Most cities increase mortgage down-payment requirements in November, with the only exception of Beijing, which increases them in March. For that reason, the visual analysis of Figure 1 is focused on the last quarter of 2013. In the tests reported in Tables 3 and 4, however, Beijing is considered a treated city starting in the second quarter of 2013.

25-90% faster than at the control cities. These findings are in line with our key predictions, and provide a first piece of evidence consistent with P2P lending being used to circumvent regulatory credit supply constraints.

Our subsequent tests validate this visual check, and strengthen the case for a causal interpretation. City- and borrower-lender level regressions confirm the evidence from Figure 1. In particular, the borrower-lender level regressions allow us to trace the impact of the P2P lending demand shock, while holding credit supply fixed with lender fixed effects. This allows us to precisely estimate the capacity of P2P lending to contribute to household leverage. Our estimates imply that the increase in P2P borrowing we observe accounts for about 13% of the increase in down-payment requirements. Given that Renrendai, though an important market player, is but one of a large number of P2P lending platforms active in China, and that borrowers may be able to obtain credit on multiple platforms at the same time (Aggarwal and Stein (2016)), this estimate provides a lower bound on the importance of P2P lending as a channel to undermine regulatory intervention.

Our results also suggest that P2P lenders fail to adjust their screening and loan pricing decisions in the face of the influx of borrowers seeking to circumvent down-payment requirements. We find little evidence of changes in the credit scores and rate of on-site verification for borrowers who obtain a loan after the 2013 episode (tighter screening would imply increases for both), nor do we observe any significant changes in loan yields or maturities. This is in spite of the fact that default rates increase, driven primarily by “new” borrowers, who come to the P2P platform only after November 2013. These results suggests that lenders may have an “inflexible” lending technology and do not adjust their lending decisions, even though they are making riskier loans.

We validate this analysis studying a symmetric change in regulation, which takes place in September 2015. On that month, all the city governments in China, with the exceptions of Beijing, Guangzhou, Sanya, Shanghai, and Shenzhen, impose a 16.7% reduction in minimum down-payment requirements (from 30% to 25% of the property's value), in this case for first home purchases. In this case the demand for P2P lending at the treated cities decreases, reversing the effects observed around the 2013 episode.

Our findings make three main contributions to the literature. First, they contribute to the growing literature on the regulatory challenges posed by the disintermediation of financial services. One could view FinTech, and in particular P2P lending, as a form of shadow banking. Regulatory arbitrage has long been considered one of the main drivers of the growth of shadow banking. Interestingly, however, the literature has focused on the elusion of regulatory constraints by financial intermediaries such as banks, i.e. on the side of credit *supply* (Adrian and Ashcroft (2012), Plantin (2014)). Our results are consistent with the view that regulatory arbitrage on the side of credit *demand* can also be economically very relevant.

Second, our test speaks to the ongoing debate on the systemic impact of household debt. Much of the literature has focused on U.S. data, and two views prevail. One view focuses on credit supply, and blames financial innovation and incentives in the financial sector for the buildup of mortgage debt leading to the 2007-2008 crisis (Mian and Sufi (2009), Claessens, Dell'Arriccia, Igan, and Laeven (2010)). A second view focuses on credit demand, on the grounds that households leverage growth has encompassed not only lower-income borrowers, but also middle-class households ((Adelino, Schoar, and Severino (2012, 2016), Foote, Gerardi, and Willen (2012), Foote, Loewenstein, and Willen (2016)). Our test presents fresh evidence from a different context – China – and time period – 2010-2016. Our findings highlight the role of both credit demand and credit supply. Credit supply factors, namely the presence of a new technology in the form of P2P platforms, offers new sources of credit to individuals. At the same time, we also show that households leverage builds on credit demand, possibly driven by speculation in the real estate market.

Third, our paper contributes to the literature on the drivers of household leverage. Low household financial literacy and ease of access to debt can lead to over-indebtedness, increasing the exposure of households to negative shocks (Lusardi and Tufano (2009)). The real estate market, at the center of our test, is a key driver of household indebtedness, at least in the U.S.: Mian and Sufi (2011) estimate that homeowners borrow 25-30 cents for every dollar increase in home equity; and Crowe and Ramcharan (2013) document that U.S. P2P borrowers experience increasing borrowing costs when real estate prices decline. Our results show that financial innovation and the disintermediation of financial services, combined with traditional mortgage lending, can contribute to the buildup of household leverage.

The remainder of the paper is organized as follows. Section II presents our data and discusses our identification strategy. Section III lays out our empirical predictions, with the aid of a simple model based on the Holmstrom and Tirole (1997) framework. Section IV reports our baseline findings on changes in P2P lending volumes around the 2013 increase in down-payment requirements, and section V changes in loan pricing and screening in the P2P lending market. Section VI presents similar tests around the 2015 decrease in down-payment requirements. Section VII concludes.

II. Data and identification

A. Data

We base our analysis on a large, loan application-level database from a Chinese online P2P lending company, Renrendai. Renrendai was launched in 2010, and quickly developed into a leading P2P lending platform, with cumulative turnover of $3.7bn (as of February 2017) and over 3 million registered accounts (2016). Among the over 2,000 Chinese P2P lending companies active as of December 2016, Renrendai ranks, by turnover, in the top 1%.

Our database spans the period from October 2010, when the platform first opens to the public, until November 2016. In total, the dataset contains 909,649 loan applications, made by 703,028 individual borrowers, and involving 277,761 lenders. Table 1 reports summary statistics.

The average loan has a size of RMB 59,674 ($8,730), with an annualized interest rate of 12.5% and duration 27 months, and a loan face value of about 40% of the borrower's annual income. In comparison, Morse (2015) reports average interest rates of about 14%, loan duration of 41 months, and loan face value of 20.5% of the borrower's annual income. We thus observe higher loan-to-income ratios, shorter durations, but similar interest rates as in the U.S. There is also sparse information on the purpose of the loans; the most common purposes are "Short Term Liquidity Needs" (48%), "Consumption/General" (25.7%), and "Entrepreneurship" (8.8%). In their survey of P2P lending in China, Deer, Mi, and Yuxin (2016) find that 51% of survey participants claim to use P2P lending to "accumulate credit worthiness," consistent with borrowing to meet a down-payment requirement, as in the 2013 episode described above. The data also report each borrower's credit score from the Credit Reference Center at the People's Bank of China. There appears to be little variation in credit scores: the average score is 172 (with standard deviation about 30), the median is 180, and the maximum is 181.

For each borrower in our data, we are able to observe a number of characteristics including demographics (gender, age, city of residence, etc.), and income level (Table 1B). A number of additional data items are disclosed by the borrowers on a voluntary basis, including education, home ownership, and whether or not they have a mortgage. Average borrower age is about 38 years; around 50% of borrowers have a college degree, and 64% are male. Unlike in the U.S. (Balyuk (2016)), the median borrower is a home owner, and about 69% of borrowers who are home owners have a mortgage. Disclosing more information allows the borrower to obtain a higher credit score on Renrendai's internal rating system, so that borrowers have an incentive to greater disclosure. In our data, 99.86% of all successful loan applications are associated with borrowers who disclose these non-mandatory items. The median borrower in our data only obtains one loan; there are, however, repeat borrowers, with up to 148 loans in their history on Renrendai.

Similar to studies based on U.S. P2P lending data (e.g. Balyuk (2016), Morse (2015)), we are not able to directly observe lender characteristics, but we can characterize them by looking at the features of their loan portfolios. In Table 1C, we look at the characteristics of the *average* lender on a given loan (the mean number of lenders per loan is 223; median: 149). On average, lenders hold a portfolio of 234 loans, with a total face value of RMB 387,978 ($58,197). Portfolios are generally diversified, with an HHI concentration index of 0.014 on average, and the average lender on a given loan has an experience on Renrendai of about 7 months. Finally, over a large number of loans are allocated to lenders via Uplan (U计划), Renrendai's embedded matching algorithm. Lenders can choose to make their loans directly to borrowers, or delegate the allocation of their funds across different loans to Uplan, an algorithm that matches lenders to borrowers mostly based on returns and maturity preference parameters set by the lender. Over 60% of all loans are made via Uplan.

B. Identification approach

The features of our data help us address the identification challenges discussed in the introduction..

In particular, to each lender on the Renrendai platform is associated a unique ID code, and the typical lender invests in multiple loans at the same time. This allows us to address the second empirical challenge discussed in the introduction, and control for unobserved lender heterogeneity by holding credit supply fixed with a fixed effects strategy. Intuitively, our proposed test compares two loans, made by the *same P2P lender, at the same time*, to two different borrowers, Fang and Wei. Fang is exposed to the increase in down-payment requirements, Wei is not. Because the P2P lender is the same on both loans, any factor affecting the supply of credit from her, related e.g. to her lending capacity, market strategy, technology etc. can thus be ruled out, allowing us to focus on the difference in credit demand between borrowers Fang and Wei. Operationally, we exploit the wealth of information at our disposal by running our tests on loan lender level data, with lender × date fixed effects.[8]

Our test thus examines changes in P2P lending applications, volumes, and other characteristics, comparing affected and un-affected real estate markets around the 2013 and 2015 changes in minimum mortgage down-payment requirements described in section II. The baseline test takes the form of a classic difference-in-differences regression:

$$L_{blt} = \alpha + \beta Treated_{bt} + \gamma Post_t + \delta(Treated_{bt} \times Post_t) + \mu' x_{blt} + \varepsilon_{blt} \qquad (1)$$

where L_{blt} denotes a loan (application) associated with borrower b and lender l at time t. $Treated$ is an indicator variable equal to 1 if the borrower is located in one of the cities affected by the change in minimum down-payment requirements. $Post$ is an indicator variable equal to 1 in the period subsequent to the change in down-payment requirements. To be immune to the Bertrand, Duflo, and Mullainathan (2004) critique of standard errors in difference-in-differences tests, we collapse the data and take averages over two periods, before and after the change in down-payment requirements, and take first differences, estimating:

$$\Delta L_{bl} = \delta Treated_{bt} + \mu' \Delta x_{bl} + \eta_{bl} \qquad (1')$$

where ΔL denotes the change in loan applications around the regulation change, associated with borrower b and lender l.

x is a vector of control variables. Given the wealth of data at our disposal, we are going to be able to estimate model (1)-(1') at different levels of (dis)aggregation of the data, allowing to control for alternative potential confounding factors. In the simplest specification, we aggregate equation (1') to the city-date level, i.e. studying the behavior of all loans (applications) in a given city at a given point in time

[8] This approach is close in spirit to the fixed effects strategies adopted in the literature on bank liquidity shocks (e.g. Khwaja and Mian (2008); Schnabl (2012)). Note, however, that studies in that literature typically control for *borrower* fixed effects, as their objective is to hold credit demand constant, to examine the effects of credit supply shocks. In our case, we want to hold credit supply constant, and thus control for *lender* fixed effects.

around each change in down-payment requirements. In that case, x only contains data on city GDP and population.

In a second specification, we estimate model (1) on the individual loan-lender level, i.e. where each observation corresponds to a given loan, associated with a given lender and borrower. This specification allows us to exploit the full depth of our data, and hold the credit supply curve fixed, saturating the model with lender × date fixed effects as discussed above (this is equivalent to including lender fixed effects in equation (1')).

The key questions are, of course, what we expect to observe when estimating model (1), and how the results of this test can inform us regarding the capacity of P2P lending to generate credit (and, potentially, undermine policy interventions in credit markets). In the next section, we develop a simple model to specify the restrictions that economic theory imposes on the data, to help us develop a set of testable predictions.

III. Predicted impact of the shock

We analyze the impact of the disintermediating P2P lenders on the effectiveness of an increase in down-payment requirements, designed to limit credit growth, using a simple framework that builds on Holmstrom and Tirole's (1997) workhorse fixed investment model. The rise in down-payment requirements to borrow from traditional lenders is analogous to a "collateral squeeze," which curbs credit in Holmstrom and Tirole's model. We show that the availability of P2P lending allows borrowers to circumvent the collateral squeeze, sterilizing its effects, such that the levels of new credit and defaults are unaffected by it, whereas aggregate interest costs rise. These results allow us to formulate the key empirical predictions for our proposed test.

First, we consider an economy populated by households (borrowers) and competitive traditional, regulated lenders ("banks"). At a later stage, we introduce disintermediating ("P2P") lenders. Households seek credit to acquire real estate, and when borrowing from a bank they are subject to an endogenous down-payment requirement $\bar{A}$ (derived below), plus an additional margin δ imposed by the regulator. We model a "collateral squeeze" as an increase in δ, and study its effects on the total amount of debt and promised interest payments level in the economy.

As in Holmstrom and Tirole (1997), borrowers are subject to moral hazard. They are able to generate future cash flows $Y \in \{0, y\}$, which they will use to pay back their loans. The probability of positive cash flows $\Pr(Y = y) = p$ takes values in $\{p_L, p_H\}$, with $p_H - p_L = \Delta_p > 0$. A borrower needs to exert "effort" to raise the success probability to p_H, and the borrower's utility from not exerting effort is B.

Each would-be borrower has assets-in-place A, corresponding to her ability to meet a down-payment requirement, and needs to borrow $I - A$ to make her real estate purchase. If the borrower does not default, she splits her cash flow with the bank such that $y = d_b + d_l$. If the borrower defaults, the bank recovers a value $R < I$ (e.g. as the result of a foreclosure process).[9] R is exogenously given.[10] Intuitively, the bank wants to induce p_H, providing the borrower with an incentive contract.

The participation constraint for the bank is $p_H d_l + (1 - p_H)R \geq I - A$, i.e. the bank must expect a larger payoff if it makes the loan than if it holds on to its cash $I - A$. This implies:

$$d_l \geq \frac{1}{p_H}[I - A - (1 - p_H)R]. \tag{2}$$

Since banks are competitive, (2) holds with equality. The incentive compatibility constraint for the borrower is $p_H d_b \geq p_L d_b + B$, i.e. the borrower must prefer to exert effort, so that:

[9] This ingredient is not present in Holmstrom and Tirole's (1997) original formulation. We introduce it for two reasons. First, it simplifies the exposition in our setting. Second, it better reflects the reality of real estate mortgages, where the lending bank's recovery can correspond to the value of the property, following the foreclosure.

[10] One could think of an extension of this analysis where the value of R is determined in equilibrium. Household leverage could then affect the value of collateral R and impose fire sale externalities, similar to the arguments of Shleifer and Vishny (1992). Such externalities could provide a rationale for the regulator's intervention (i.e., raising δ with the aim of limiting credit).

$$d_b \geq B/\Delta_p. \tag{3}$$

Combining (2) and (3) with the resource constraint $y = d_l + d_b$, and assuming $y \geq B/\Delta_p + d_l$, we have the following condition for the bank to make a loan:

$$A \geq \bar{A} = I - p_H\left[y - \frac{B}{\Delta_p} + (1 - p_H)\frac{R}{p_h}\right] \tag{4}$$

Expression (4) implies that only borrowers with sufficiently high assets-in-place (i.e. able to meet the down-payment requirements) obtain credit.

To analyze the general equilibrium of the credit market in this setting, suppose that there is a continuum of borrowers indexed by their assets-in-place A, distributed according to a cdf $G(A)$. The total amount of credit in equilibrium is then $I[1 - G(\bar{A})]$. Denoting the bank's required interest rate by i_l, by definition $d_l = (I - \bar{A})(1 + i_l)$, so that from expression (2) we have:

$$i_l = \frac{1}{p_H}\left[1 - \frac{R(1-p_H)}{I-\bar{A}}\right] - 1 \tag{5}$$

and the aggregate interest owed in the economy is $i_l[1 - G(\bar{A})]$.

Consider now the effects of a "collateral squeeze," in which the regulator mandates that borrowers possess an additional $\delta > 0$ over and above $\bar{A}$, in the form of a mandatory minimum down-payment requirement. The resulting total amount of lending is $I[1 - G(\bar{A} + \delta)]$. As the function $G(\cdot)$ is monotone increasing, this is less than $I[1 - G(\bar{A})]$, i.e. the squeeze curbs the level of debt in the economy. Because the bank has a smaller exposure to each borrower, moreover, interest rates decrease via expression (5), and the aggregate interest costs are reduced. Finally, because there are fewer borrowers, there are also fewer aggregate defaults $(1 - p_H)[1 - G(\bar{A} + \delta)]$. In sum: imposing a collateral squeeze reduces new credit, as well as aggregate interest payments and aggregate defaults.

What happens when unregulated P2P lenders are introduced? The P2P lenders are assumed to be competitive, as well as "small," in the sense that they cannot lend more than δ to any borrower. These assumptions mimic the features of the P2P lending market in China (Deer, Mi, and Yuxin (2015)). A simple strategy for a would-be borrower who fails to obtain credit from the bank because her assets-in-place are below $\bar{A} + \delta$, then, is to borrow $\bar{A} + \delta - A$ from the P2P lenders, so as to be able to make the full $\bar{A} + \delta$ down-payment to the bank. We study whether this strategy can be sustained in equilibrium, and its implications.

There are two main differences between P2P lenders and banks. First, the P2P lenders are not collateralized, i.e. in the event of default their payoff is equal to 0. Second, they do not condition their lending decisions on the borrower's assets-in-place, but simply take her default risk as given. This implies that the participation constraint for the P2P lenders is:

$$p_H d_{P2P} \geq \bar{A} + \delta - A, \tag{6}$$

where the P2P lender payoff is scaled by p_H because the borrower also receives credit from the bank, which provides the incentive to exert effort.[11]

For large enough y, this will be true in equilibrium. Because the P2P lenders are competitive, the constraint (6) holds with equality, and $d_{P2P} = (\bar{A} + \delta - A)/p_H$. The participation constraint for the bank (2) is now modified as $d_l = \frac{1}{p_H}[I - (\bar{A} + \delta) - (1 - p_H)R]$, and the incentive constraint for borrowers remains $d_b \geq B/\Delta_p$. The minimum level of assets-in-place $\bar{A}$ required to obtain credit from the bank is again pinned down by the resource constraint $y = d_l + d_{P2P} + d_b$, and because the $\bar{A} + \delta$ terms in d_l and d_{P2P} cancel out, $\bar{A}$ is again given by expression (4). In other words, regardless of the size of the collateral squeeze δ, an identical mass $1 - G(\bar{A})$ of borrowers obtains credit, and the level of the debt in the economy is unchanged. Similarly, the expected number of defaults remains $(1 - p_H)[1 - G(\bar{A})]$.

[11] As we verify below, in equilibrium borrowers turn to the bank first, and only if they do not have sufficient assets-in-place A they also borrow from the P2P lenders. This allows the P2P lenders to "free ride" on the incentives provided by the bank. P2P credit is still more expensive, because the recovery under default is 0 (while the bank recovers R). Alternatively, one could assume that the probability of default remain "low" (p_L) for P2P loans, without changing the main conclusions.

What changes is aggregate interest payments. The interest rate demanded by the P2P lenders, implied by (6), is: $i_{P2P} = \frac{1}{p_H} - 1$. This is larger than i_l, because of the recovery value R. Aggregate interest costs, therefore, increase to:

$$\underbrace{i_l \times [1 - G(\bar{A} + \delta)]}_{\text{To banks}} + \underbrace{i_{P2P} \times [G(\bar{A} + \delta) - G(\bar{A})]}_{\text{To P2P lenders}}. \tag{7}$$

In sum: the objective of the collateral squeeze is to curb new credit, reducing aggregate defaults and aggregate interest costs. The availability of P2P credit sterilizes the collateral squeeze, leaving new credit and aggregate defaults unchanged, and raising the aggregate interest costs.

This analysis allows us to formulate our key empirical predictions. The 2013 increase in down-payment requirements corresponds to an increase in δ. Changes in δ do not affect the overall level of credit in the economy, but simply shift demand into and out of P2P lending. Therefore: Following the 2013 increase in down-payment requirements, we will observe a larger number of new P2P loans (or a larger RMB volume of new P2P loans) in cities that raise mortgage down-payment requirements (treatment group) than in other cities (control group).

This model provides a simple framework to form expectations on the impact of P2P lending on the effectiveness of the 2013 (and, in a further test described below, 2015) policy intervention in the mortgage markets. A byproduct of its simplicity is that aggregate defaults remain unchanged at $(1 - p_H)[1 - G(\bar{A})]$, because individual borrower default risk is constant. A more flexible model might generate increasing default rates as borrowers turn to P2P lending. At this stage, we feel that such a model is beyond the scope of our study, as our focus is mainly empirical; a future draft of the paper may explore changes to the theoretical framework in this direction.

IV. Baseline tests

A. Comparison of treatment and control groups

Our main tests are focused on the 2013 increase in down-payment requirements. The cities that experience it include four of the ten largest cities in China (Beijing, Guangzhou, Shanghai, and Shenzhen)[12] and make up about 9% of the population of urban China in our sample on average.[13] In addition, both "tier-1" (Beijing, Guangzhou, Shanghai, and Shenzhen) and "tier-2" (Changsha, Hangzhou, Nanjing, Shenyang, and Wuhan) cities experience the treatment. We take all other Chinese cities with active borrowers on Renrendai and population over 5 million as our control group.

In Table 2, we compare the loans associated with the treatment and control cities along observable dimensions, prior to November 2013 when the increase in down-payment requirements is announced for most treated cities. Panel A focuses on borrowers. Borrowers from treated and control cities do not exhibit significant differences in terms of monthly income (RMB 11,216 and 11,872 on average), age (39.18 and 38.73 years), gender (59% and 57% males), or the number of loan applications since registering on RenrenDai (1.5 and 2). Treated borrowers are modestly more likely to have a college degree (50.6% have one, compared to 45.1% for the control group; t-stat: 1.695), and less likely to be home owners (20.9%, compared to 31.2% for the control group; t-stat: -2.107). Panel B compares lenders across the two groups. In terms of portfolio size, concentration, experience, and participation to Uplan, there are no significant differences between the treated and control groups, in statistical as well as economic terms.

In sum, we do not observe large differences along observable dimensions between treatment and control groups prior to the increase in down-payment requirements of November 2013. That confirms the intuition from Figure 1, which shows parallel trends in P2P lending in the two groups in the pre-down-payment increase period, and validates the difference-in-differences setting for our test.

[12] Communiqué of the National Bureau of Statistics of the People's Republic of China on the Major Figures of the 2010 Population Census.

[13] We restrict the sample to cities with an average population of at least 5 million during our sample period (all the results are robust to including smaller cities).

B. Regression evidence

We run a set of preliminary regressions on city-level data. We estimate model (1') by time-averaging, collapsing the data, and taking first differences, as described above, to control for serially correlated standard errors (Bertrand, Duflo, and Mullainathan (2004)).

The results are reported in Table 3. The estimates support the evidence from Figure 1 described in the introduction, as well as the arguments illustrated in the previous section. They imply that, following the 2013 rise in down-payment requirements, the RMB volume of P2P loans in cities affected by the rise increase by 40% on an annual basis (specification (2)). Compared to the average loan size of about RMB 60,000 ($8,777), this corresponds to a RMB 24,000 ($3,600) increase.

The value of a medium-size apartment (750 sq. ft.) in Shanghai, one of our treatment group cities, is RMB 1.8 m (about $260,000), so that the increase we document accounts for 13% (= RMB 24,000 / RMB 180,000) of the 10-percentage point increase in down-payment requirements. Given that Renrendai, though an important market player, is but one of a large number of P2P lending platforms active in China, and that borrowers may be able to obtain credit on multiple platforms at the same time (Aggarwal and Stein (2016)), these figures provide a lower bound on the importance of P2P lending as a channel to circumvent the new requirement.

The evidence from these regressions is consistent with the notion that borrowers use P2P lending to circumvent the increase in down-payment requirements. An increase in P2P loans, however, is in general the result of a combination of shifts in credit demand and credit supply. For instance, a faster development of P2P lending, or a greater popularity of P2P as a form of investment at the treated cities, might generate similar effects as the ones we observed. To control for credit supply side effects, we exploit the depth of our data, and estimate model (1) on data matching individual lenders and borrowers, including lender × date fixed effects. As discussed above, this allows us to hold credit supply fixed, and isolate the effect of a shock to credit demand.

The estimates are reported in Table 4. Specifications (1)-(3) include lender × date fixed effects; specification (4) reports the corresponding estimates without them. Overall, the estimates are in line with the findings discussed in the previous section, and consistent with an increase in P2P lending demand to circumvent the down-payment requirement increase. Economically, the effects are also meaningful: they imply a 3% monthly increase in P2P lending at the treated cities, or 36% on an annual basis. Based on a back-of-the-envelope calculation similar to the one discussed above, this suggests that the P2P lending channel captures about 12% of the increased down-payment requirement, similar to the aggregate results.

The structure of the data also allows us to separately analyze the intensive margin (borrowers already active on Renrendai increase their borrowing) and the extensive margin (new borrowers turn to Renrendai once down-payment requirements increase). To do so, we estimate two additional regressions, in columns (5) and (6). In column (5) (intensive margin), the sample is restricted to borrowers who are active on Renrendai (have at least one loan) both before and after November 2013. In column (6) (extensive margin), the sample is restricted to borrowers who are active (have at least one loan) only before or only after 2013. The coefficient estimate on $Treated$ in the intensive margin regression is 0.009, indistinguishable from zero; the corresponding estimate in the extensive margin regression is 0.029 (t-stat: 2.42). The difference between the two coefficients is approximately equal to the estimated coefficients on $Treated$ in specifications (1)-(3), suggesting that the effect is driven by the *extensive* margin: in other words, the influx of new borrowers after the 2013 increase in down-payment requirements explains our baseline effect.

Further analysis based on borrower and lender characteristics, reported in Table 5, provides a richer characterization of these findings. In Table 5A, we document that the increase in P2P borrowing at the treated cities is driven by borrowers who already own a home (specifications (1)-(2)). We also find that our baseline effect is driven by cities where house price growth over the 18-month period prior to

November 2013 has been above median.[14] These findings corroborate the link between the increase in P2P credit at the treated cities and the increase in down-payment requirements in November 2013, given that the new regulation only applies to second-home mortgages, and was aimed at overheating real estate markets.

In Table 5B, we partition the sample based on lender characteristics: lending via Uplan/direct lending, experience, portfolio size, and portfolio concentration. At a first glance, Table 5B shows that borrowers in treated cities receive financing from lenders of any type: every coefficient on the variable "Treated" is positive and statistically significant. The effect appears to be more pronounced for lenders that lend via Uplan, with less experience, and with a larger and more diversified portfolio of P2P loans. A possible interpretation of these results is that diversified lenders, who generally have a smaller incentive to monitor and screen their loans, are those more likely to fund "treated borrowers". These lenders also tend to invest large sums into the platform, but they look different from a traditional bank as they do not appear to produce information about their borrowers.

Taken together, these findings suggest that P2P lending supply responds to the credit demand generated by the 2013 increase in down-payment requirements as predicted by our discussion of Section III. P2P lenders are able to supply an economically substantial amount of credit, accounting for 12% of the implied increase in borrowing as per our back-of-the-envelope calculation. The expansion of credit is driven by borrowers from cities that experience faster house prices growth, as well as by a broad range of lenders.[15]

[14] In Table 5A, we split the sample only in the treated group and not in the control group. In this way, we can keep the control group constant between subsamples and see whether the changes in down payment requirements affect lending only via home owners living in the treated cities or only via treated cities with higher house prices forecasts.

[15] Throughout our analysis we implicitly assume that borrowers use P2P funds to buy a house in the city where they live. A possible concern is that borrowers in control cities borrow funds on Renrendai to buy a house in a treated city. In principle, this possibility would make our control and treatment groups more alike, suggesting that our estimates represent a lower bound of the effects of interest. Moreover, every city in our treated group has home purchase restrictions in place that prevent residents from other cities to buy a second house in the areas under their jurisdiction. For instance, only a registered resident in Shenzen is allowed to buy a second house in Shenzen, ruling out the possibility that a P2P borrower in, say, Chengdu (a city in our control group) may borrow on the platform to fulfil the down payment requirement set by another city.

V. Other loan features; loan performance

A. Pricing, duration, and borrower characteristics

P2P lenders may respond to an influx of loan applications following the 2013 down-payment requirement increase by adjusting lending volumes (as documented in the previous section), as well as loan contract features. We consider three central features of loan contracts: the degree of screening to which the borrower is subject, pricing, and duration.

Although the treated cities appear to generate an abnormal amount of P2P borrowing after 2013, we find that P2P lenders do not appear to alter their screening in response. Our first measure of screening is on-site verification. Borrowers on Renrendai self-declare their characteristics such as income, age, etc. In addition, they may also provide on-site verification, whereby an officer from Renrendai verifies that the information provided is true, by visiting the borrowers at their stated address. If lenders respond to the influx of new borrowers by stepping up screening and tightening their lending standards, they may more frequently demand on-site verification in order to invest in a given loan. We should therefore expect higher rates of on-site verification among the loans made after the last quarter of 2013. We detect, however, no evidence of change in on-site verification rates in Table 6 (in fact, we observe a slight, statistically insignificant, decrease, specifications (7)-(8)).

We do find, on the other hand, some evidence of a worsening borrower credit score. The estimates of Table 6 indicate that the credit score drops by nearly 3% for the treated cities, compared to an average of 171.9. Interestingly, the effect largely disappears once we control for borrower fixed effects, suggesting that it is driven by the extensive margin, i.e. “new” borrowers. Having said that, the effect is economically minuscule, suggesting that the lenders simply do not become more discriminating after November 2013.

Consistent with this picture, the pricing and duration of loan contracts issued after 2013 do not change appreciably. We find no significant changes in yield spreads, nor in duration, after 2013. In sum, P2P lenders treat the influx of borrowers from the treated cities just like their old borrowers, and lend to them conditions that are no different. This suggest that lenders make no adjustments to their lending terms following 2013. The interesting question is, of course, whether this can be rationalized ex post, for instance because the "new" loans perform similarly to the "old" ones.

B. Loan performance

We test for this possibility by looking at P2P two measures of performance: delinquencies (the proportion of months, over the loan's life, during which the borrower is delinquent) and loan default rates. The sample size shrinks in this case, because of a truncation problem: for some ongoing loans, default may simply not have been declared yet.

The evidence, reported in Table 7A, indicates a deteriorating loan performance at the treated cities following 2013. We observe an increase in delinquency rates by 1 percentage point (specification (1)) and in default rates by 0.90 percentage points. Similar to the estimates reported by Morse (2015) for the U.S., default rates are on average about 2% among Renrendai loans (Table 1).[16] Our estimates imply, therefore, that defaults increase by 45% in relative terms, which appears economically very relevant. Here too, we find that the effect is entirely driven by the extensive margin, and disappears once we control for borrower fixed effects. The interpretation is that the increased default rates occur primarily among "new" borrowers, who register on Renrendai or start borrowing after 2013, and are thus more likely driven by the minimum down-payment increase.

[16] In the second half of 2015, there was a wave of defaults on P2P loans across mainland China, with much higher default rates than the 2% average associated with the entire sample ("China's Unregulated P2P Lending Sites are Still Spreading Financial Instability", *China Economic Review* July 28, 2015; "China Imposes Caps on P2P Loans to Curb Shadow-Banking Risks", *Bloomberg News*, August 24, 2016). We are able to observe the increase in defaults in our data; however, given its timing, it has a minimal impact on our estimates around the 2013 increase in minimum down-payment requirements.

We further find, in Table 7B (specifications (1)-(2)), that the increase in defaults is mainly associated with borrowers who are home owners. This is consistent with our earlier results, as home owners are more likely attempting to circumvent the minimum down-payment increase. Moreover, using an AR(1) model for house price indexes, we estimate house price growth forecasts for each of our treated cities. We then compute forecast errors, and run separate tests for cities where the forecast proved to be higher/lower than actual house price growth (specifications (3)-(4)). We find that the increase in defaults is estimated more precisely in cities where house price growth underperforms the forecast.

Taken together, the evidence presented in this section and the previous one suggests that: (i) Following the 2013 increase in minimum down-payment requirements, P2P borrowing rises abnormally at the treated cities; (ii) P2P lenders do not respond by adjusting their screening procedures, nor do they alter the pricing and duration of their loans in response; and (iii) Default rates among "new" post-2013 borrowers are systematically higher.

VI. Evidence on the 2015 episode

As we mentioned above, in September 2015 a reverse policy intervention is implemented across the country. As part of a broader stimulus package, minimum down-payment requirements on first homes are lowered by 16.7%, from 30% to 25% of the asset's purchase value, in all cities except Beijing, Guangzhou, Sanya, Shanghai, and Shenzhen. Based on the arguments of Section III, this should curb the demand for unregulated P2P lending.

Two caveats are in order here, to correctly interpret the tests we are about to discuss. First, the demand for P2P lending will decrease, under the assumption that the existing credit demand as of September 2015 incorporates a "P2P component" of borrowers who resort to P2P to meet existing down-payment requirements. This appears plausible, based on our findings on the effects of the 2013 policy intervention discussed in the preceding sections. Second, if the 2013 episode provides a relatively "clean" experiment based on the unintended effects of regulation, in 2015 the credit authorities are likely aware of the potential role of P2P lending.

Bearing these caveats in mind, we run tests similar to the ones presented in sections IV and V. First, we examine changes in lending volumes following September 2015, comparing "treated" and "control" cities, where the treatment group includes all Chinese cities with the exception of Beijing, Guangzhou, Sanya, Shanghai, and Shenzhen, which form the control group. The results are illustrated in Table 8A. Consistent with our expectations, we find that P2P lending drops at the treated cities, mainly driven by the extensive margin. In other words, some borrowers abandon the P2P channel altogether. In economic terms, the effects are similar to the ones presented in section IV, but with the reverse sign.

Second, we look at lending outcomes, in Table 8B. Once again, we do not observe large changes in screening: the coefficient estimate in specification (4) (on-site verification), although statistically significant is economically small at 2.4 percentage points; furthermore, we do not observe any significant changes in credit scores, and the magnitude of the coefficient estimate in specification (3) is economically negligible. Given that, following the lowering of down-payment requirement, the P2P lenders should expect *fewer* bad borrowers, there is no reason they should tighten their screening.

We do observe statistically significant changes in the loan terms (pricing and duration), but again they appear economically small. Yield spreads are reduced by about 10 bps, compared to the sample average of 7%; loan duration drops by about 2 days (0.064 months), compared to the sample average of 27 months. Taken together, these findings, as well as those of sections III and IV, suggest that P2P lenders are generally unresponsive to policy intervention, i.e. they do not condition their lending decisions to the expected "type" of borrower they may face. This is perhaps consistent with the lower sophistication typically associated with P2P lenders; on the other hand, it suggests that the benefits in terms of informal contracting and "proximate knowledge" suggested by the earlier literature may be limited.

Finally, we do not observe any material changes in delinquencies. Default rates decline by 3.8 percentage points in the treated cities, with the coefficient marginally statistically significant (with t-stat of 1.49).

VII. Conclusions

We investigate the capacity of unregulated, disintermediated P2P lending to generate excess household leverage and interfere with policy intervention in credit markets. We rely on a novel, hand-collected database containing all loan transactions at Renrendai, a leading Chinese peer-to-peer lending platform. We also focus on a policy intervention in credit markets: the increase in 2013 of down-payment requirements on second-home mortgages at several major Chinese cities. This policy intervention increases the demand for P2P credit by borrowers who try to circumvent the down-payment requirements, leaving overall credit demand unchanged. Consistent with this argument, we find evidence of increases in P2P lending at the treated cities following the 2013 episode. Importantly, the structure of our data allows us to separate credit demand and supply effects, using a fixed effects strategy – we are thus able to isolate the capacity of the P2P channel to fuel household demand for credit. We validate this analysis with evidence from a reverse experiment in 2015, when city governments lower minimum down-payment requirements, resulting in a drop in P2P credit demand. In either episode, we find little evidence that P2P lenders adjust their policies in response to the expected characteristics of their borrowers, suggesting that the information benefits of P2P lending that have been observed by part of the literature may be limited.

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Table 1 Summary statistics

The table reports summary statistics. Panel A describes loan characteristics, panel B borrower characteristics, and panel C lender characteristics. All variables are defined in detail in Appendix A. The sample consists of all loans on the Renrendai platform, over the period 2011Q1-2015Q2 for borrowers located in metropolitan areas in mainland China with population above 5 million.

	Mean	**St. dev.**	**Min**	**Median**	**Max**	**N**
A. Loan characteristics						
Loan amount (RMB)	59,674	53,816	3,000	52,900	3,000,000	107,502
Interest rate (%)	12.49	1.01	7.00	12.60	24.40	107,502
Interest rate spread (%)	7.78	1.07	2.89	7.84	19.81	107,502
Duration (months)	27.06	9.78	1	24	36	107,502
On-site verification (Y/N)	0.77	0.42	0	1	1	107,457
Borrower credit score	171.82	29.71	0	180	181	107,339
Loan Delinquent (0/1)	0.04	0.21	0	0	1	107,502
Proportion of Months Delinquent (%)	1.96	11.35	0.00	0.00	100	107,502
Default (0/1)	0.02	0.14	0	0	1	78,289
B. Borrower characteristics						
Income (RMB)	11,334	13,254	0	5,000	50,000	107,494
Age	37.74	36.00	8.41	23	56	107,502
College degree (0/1)	0.52	0.50	0	1	1	107,498
Male (0/1)	0.64	0.48	0	1	1	107,502
House owner status (0/1/2)	0.86	0.91	0	1	2	107,502
Number of applications since registration	1.35	3.54	1	1	148	107,502
C. Lender characteristics						
Portfolio size (RMB)	387,978	485,871	4,689	289,434	4,215,150	107,502
Portfolio size (nr. loans)	234.53	156.08	4.00	199.99	1975	107,502
Uplan lending (% of RMB)	67.18	31.26	0	86.02	100	107,502
Uplan lending (% of loans made)	71.94	30.49	0	91.20	100	107,502
Portfolio concentration (HHI)	0.007	0.019	0	0.001	1	107,502
Experience (months since first loan)	6.86	4.31	0	5.80	37	107,502

Table 2 Comparison of treatment and control groups pre-November 2013

The table compares the characteristics of borrowers and lenders on loans associated with cities in the treatment (Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenyang, Shenzhen, and Wuhan) and control groups (all other Chinese cities with over 5 million inhabitants) prior to the November 2013 increase in minimum down-payment requirement. The column labeled "Treated" reports the average of each characteristic for the treatment group, the column "Control" for the control group, the column "Difference" their difference, and the column "t-statistic" the t-test statistic for the difference, based on standard errors clustered around cities.

	Treated	**Control**	**Difference**	**t-statistic**
A. Borrower characteristics				
Income (RMB)	11,216	11,872	-656.27	-0.731
Age	39.18	38.73	0.449	1.175
College degree (0/1)	0.51	0.45	0.06	1.695*
Male (0/1)	0.59	0.57	0.02	0.877
House owner status (0/1/2)	0.21	0.31	-0.10	-2.107**
Number of applications since registration	1.51	2.06	-0.56	-0.974
B. Lender characteristics				
Portfolio size (RMB)	468,649	492,152	23,503	0.833
Portfolio size (nr. loans)	268.2	275.6	7.385	0.579
Uplan lending (% of RMB)	68.93	71.64	2.712	0.640
Uplan lending (% of loans made)	72.76	75.57	2.805	0.655
Portfolio concentration (HHI)	0.0061	0.0055	-0.001	-0.530
Experience (months since first loan)	4.492	4.396	-0.095	-0.745

Table 3 P2P lending around the 2013 increase in mortgage down-payment requirements: City level
The table reports the estimates of:

$$L_{ct} = \alpha + \beta Treated_c + \gamma Post_t + \delta(Treated_c \times Post_t) + \mu' x_{ct} + \varepsilon_{ct}$$

Each observation corresponds to a given city c on a given calendar quarter t. The dependent variable is the log-loan amount associated with the aggregate loan applications or actual loan volume in the city. $Treated$ is an indicator variable equal to 1 if the city belongs to the treatment group (Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenyang, Shenzhen, and Wuhan). $Post$ is an indicator variable equal to 1 over the period followinga change in mortgage down-payment requirements. In panel A, the sample period covers a window of $\pm$1 year around the down-payment increase; in panel B, $\pm$2 years. To control for serial correlation in the standard errors, we time-average and collapse the data (Bertrand, Duflo, and Mullainathan (2004)), and estimate:

$$\Delta L_c = \delta Treated_c + \mu' \Delta x_c + \eta_c$$

where ΔL_c denotes the change in log-loan amount from before to after the change in down-payment requirements. Specifications (1) and (2) focus on Renminbi lending volumes, and specifications (3) and (4) count loans and loan applications. Specifications (1) and (3) focus on loan applications, and specifications (2) and (4) restrict the focus to loans that are actually granted. In all specifications, the vector of control variables x includes province GDP and population level and past growth rates, city-level house price % growth over the past 18 months, city-level employment rate and wage level, and city-level household debt per capita and bank deposits per capita, and the standard errors (reported in parentheses) are clustered at the city level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

A. P2P lending at Renrendai, $\pm$ 1 year around down-payment requirement increase

	RMB lending volumes		**Number of loans (applications)**	
	All Applications	**Loans**	**All Applications**	**Loans**
	(1)	(2)	(3)	(4)
$Treated$	0.156***	0.099**	0.476**	0.518**
	(0.052)	(0.039)	(0.191)	(0.209)
Controls	Y	Y	Y	Y
R^2	0.58	0.44	0.60	0.46
N	53	53	53	53

B. P2P lending at Renrendai, $\pm$ 2 years around the down-payment requirement increase

	RMB lending volumes		**Number of loans (applications)**	
	All Applications	**Loans**	**All Applications**	**Loans**
	(1)	(2)	(3)	(4)
$Treated$	0.167***	0.088*	0.446**	0.409*
	(0.053)	(0.045)	(0.169)	(0.216)
Controls	Y	Y	Y	Y
R^2	0.61	0.48	0.62	0.50
N	53	53	53	53

Table 4 P2P lending around the 2013 increase in mortgage down-payment requirements: Credit volumes

The table reports the estimates of:

$$L_{lbt} = \alpha_b + \alpha_l + \alpha_t + \alpha_l \times Post_t + \delta Post_t \times Treated_{bc} + \mu' x_{bt} + \varepsilon_{lbt}$$

Each observation corresponds to a given borrower-lender pair b on a given calendar date t. The dependent variable is the log-loan amount lent to a given borrower b by a lender l. $Treated$ is an indicator variable equal to 1 if the borrower is located in a city that belongs to the treatment group (Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenyang, Shenzhen, and Wuhan). $Post$ is an indicator variable equal to 1 over the period following the change in mortgage down-payment requirements. α_b indicates borrowers fixed effects, α_l lenders fixed effects and α_t month of the year fixed effects. To control for serial correlation in the standard errors, we time-average and collapse the data (Bertrand, Duflo, and Mullainathan (2004)), and estimate:

$$\Delta L_b = \delta Treated_{bc} + \mu' \Delta x_b + \eta_b$$

where ΔL_c denotes the change in log-loan amount from before to after the change in down-payment requirements. Specifications (1)-(4) focus on Renminbi lending volumes in the full sample, specification (5) focuses on the sub-sample of borrowers who borrow on Renrendai both before and after the policy shock, and specification (6) looks at the subset of borrowers who borrow on Renrendai only before or only after the policy shock. Province controls include province GDP per capita level and GDP growth over the past 12 months, province population level and population growth over the past 12 months, and the % change of the city house prices in the previous 18 months. Labor market controls include city-level employment rate and yearly wages. Household finance controls include city-level household debt per capita and bank deposits per capita. The standard errors (reported in parentheses) are clustered at the city level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

	Full Sample				**Intensive margin**	**Extensive margin**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated$	0.020*	0.024**	0.030**	0.040**	0.009	0.029**
	(0.012)	(0.011)	(0.012)	(0.018)	(0.011)	(0.012)
Province controls	Y	Y	Y	Y	Y	Y
Labor market controls	N	Y	Y	Y	Y	Y
Household finance controls	N	N	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	N	Y	Y
R^2	0.38	0.39	0.39	0.03	0.58	0.38
N	5,051,602	5,051,602	5,051,602	5,065,546	94,894	4,939,070

Table 5 Credit volumes and borrower and lender characteristics
The table reports the estimates of regressions with identical specification as in Table 3, estimated over alternative sub-samples. Panel A focuses on borrower home ownership (Y/N) and on the borrower's city house price growth rate (High – above the median/Low – below the median). Panel B focuses on characteristics of the lender's portfolio: whether a loan is made via Uplan or direct peer-to-peer, whether the lender's experience is low or high (below/above the median), whether her portfolio is small or large (below/above the median), and whether her portfolio's concentration is low or high (below/above the median).

A. Borrower home ownership and borrower city house price growth

	Borrower home owner		**Borrower city house price growth**	
	Yes	**No**	**High**	**Low**
	(1)	(2)	(3)	(4)
$Treated$	0.041***	0.002	0.018**	0.015
	(0.012)	(0.018)	(0.008)	(0.036)
Province ctrls	Y	Y	Y	Y
Labor market ctrls	Y	Y	Y	Y
Household finance ctrls	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
R^2	0.37	0.40	0.38	0.40
N	4,162,218	4,255,312	4,352,859	4,065,767

B. Lender characteristics

	Lending channel		**Experience**		**Portfolio**		**Ptf. concentration**	
	Uplan	**Direct**	**Low**	**High**	**Small**	**Large**	**Low**	**High**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treated$	0.029**	0.017*	0.022**	0.013**	0.017**	0.032**	0.036*	0.015**
	(0.014)	(0.010)	(0.010)	(0.006)	(0.009)	(0.015)	(0.019)	(0.007)
Province ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Labor market ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Household finance ctrls	Y	Y	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.35	0.60	0.64	0.26	0.63	0.33	0.57	0.29
N	3,990,351	1,053,846	2,480,133	2,445,586	2,507,714	2,543,428	2,397,347	2,528,313

Table 6 P2P loan pricing and screening of the borrowers around the 2013 increase in down-payment requirements
The table reports the estimates of:

$$Y_{bt} = \alpha + \beta Treated_b + \gamma Post_t + \delta(Treated_b \times Post_t) + \mu' x_{bt} + \varepsilon_{bt}$$

Each observation corresponds to a given borrower b on a given calendar date t. The dependent variable Y_{bt} is the natural logarithm of the interest rate spread associated with the loan (spec. (1)-(2)), the natural logarithm of the duration of the loan ((3)-(4)), the borrower's credit score ((5)-(6)), and the on-site verification indicator ((7)-(8)). $Treated$ is an indicator variable equal to 1 if the city belongs to the treatment group (Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenyang, Shenzhen, and Wuhan). $Post$ is an indicator variable equal to 1 over the period following a change in mortgage down-payment requirements (after November 2013 for all treated cities, with the exception of Beijing, where it is equal to 1 following May 2013). In all specifications, the vector of control variables x includes city fixed effects, calendar month fixed effects, administrative region × calendar month fixed effects, province GDP and population level and past growth rates, city-level house price % growth over the past 18 months, city-level employment rate and wage level, and city-level household debt per capita and bank deposits per capita, as well as borrower age, income, college degree, gender, home ownership status, and number of applications the borrower registered on Renrendai. Specifications (2), (4), (6), and (8) also control also for borrower fixed effects. The standard errors (reported in parentheses) are clustered at the city level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

	Spread		**Duration**		**Credit Score**		**On-site Verification**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treated \times Post$	0.001	-0.002	0.022	-0.080	-0.029*	0.001	-0.051	-0.015
	(0.000)	(0.002)	(0.021)	(0.068)	(0.012)	(0.04)	(0.041)	(0.034)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FE	N	Y	N	Y	N	Y	N	Y
Region	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.52	0.78	0.50	0.89	0.44	0.99	0.51	0.98
N	98,697	4,140	98,697	4,140	98,534	4,140	98,652	4,134

Table 7 P2P Loan performance following the 2013 increase in down-payment requirements

The table reports the estimates regressions analogous to Table 5. In panel A, the dependent variable is delinquency, the proportion of months during the borrowing period in which the borrower is delinquent (spec. (1)-(2)), or a default indicator ((3)-(4)). In panel B, the dependent variable is always the default indicator, and the sample is split between loans to borrowers who own a home or not (spec. (1)-(2)), as well as between loans to borrowers located in cities with high/low (above/below the median) ex post house price forecast error. In both panels and all specifications, the standard errors (reported in parentheses) are clustered at the city level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

A. Full sample

	Delinquency		**Default**	
	(1)	(2)	(3)	(4)
$Treated \times Post$	0.010*	-0.046	0.009*	-0.075
	(0.005)	(0.043)	(0.005)	(0.049)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Borrower FE	N	Y	N	Y
Region	Y	Y	Y	Y
R^2	0.15	0.65	0.08	0.52
N	98,697	4,140	70,554	3,576

B. Borrower home ownership and house price forecast errors

	Borrower home owner		**Borrower city house price forecast error**	
	Yes	**No**	**High**	**Low**
	(1)	(2)	(3)	(4)
$Treated \times Post$	0.013*	0.010	0.009*	0.009
	(0.007)	(0.006)	(0.005)	(0.010)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Borrower FE	N	Y	N	Y
Region	Y	Y	Y	Y
R^2	0.09	0.09	0.09	0.09
N	53,540	63,190	59,465	57,265

Table 8 P2P lending around the 2015 decrease in down-payment requirements

Panel A reports the estimates of regressions analogous to Table 3, estimated around the September 2015 decrease in down-payment requirements. In this case, the $Treated$ indicator equals 1 for all Chinese cities with at least 5 million inhabitants except Beijing, Guangzhou, Shanya, Shanghai, and Shenzhen. Panel B reports the estimates of regressions analogous to Tables 5 and 6, estimated again around the September 2015 decrease in down-payment requirements. In all panels and specifications, the standard errors (reported in parentheses) are clustered at the city level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

A. Credit volumes

	Full Sample		**Intensive Margin**	**Extensive Margin**
	(1)	(2)	(3)	(4)
$Treated$	-0.048*	-0.027**	-0.017	-0.027**
	(0.028)	(0.011)	(0.013)	(0.012)
Controls	Y	Y	Y	Y
Lender FE	N	Y	Y	Y
Region FE	Y	Y	Y	Y
R^2	0.012	0.390	0.444	0.398
N	14,367,497	13,960,421	313,499	13,589,210

B. Loan pricing, screening of the borrowers, and loan performance

	Spread	**Duration**	**Credit Score**	**On-site Verification**	**Delinquency**	**Default**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated \times Post$	-0.001***	-0.064***	-0.088	-0.024**	0.006	-0.038
	(0.000)	(0.019)	(0.058)	(0.011)	(0.005)	(0.025)
Controls	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
Region × Month FE	Y	Y	Y	Y	Y	Y
R^2	0.47	0.47	0.48	0.36	0.15	0.09
N	184,433	184,433	184,417	182,680	184,433	59,730

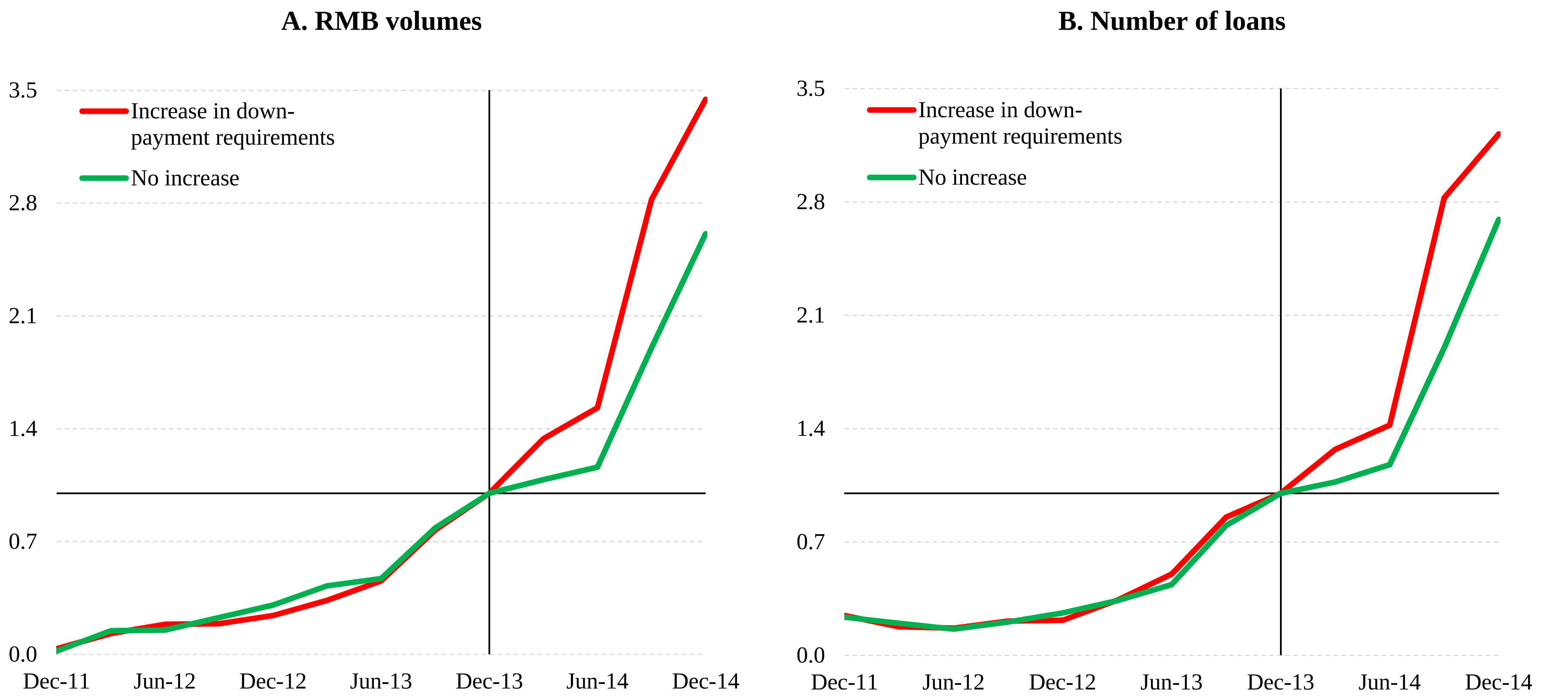

Figure 1 P2P lending at Renrendai around the 2013 increase in down-payment requirements
The graphs plot the P2P loans on the Renrendai platform, for treated and control cities, around the 2013 increase in mortgage down-payment requirements. In panel A, the vertical axis reports the city-level Renminbi loan applications volume per capita, averaged across all treated cities (Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenyang, Shenzhen, and Wuhan) and control cities (all other Chinese cities with population above 5 million). In panel B, the vertical axis reports the number of loan applications per capita, averaged across treated and control cities. We normalize each series to so as to equal 1 on the date of the change in down-payment requirements (the fourth quarter of 2013), such that the vertical axis represents the relative change in P2P loan applications compared to that date. The graph shows that, after the increase in down-payment requirements, the growth in P2P loan applications in the treated cities is higher than in the control cities.

APPENDIX: VARIABLE DEFINITIONS

VARIABLE	Definition
A. Loan characteristics	
Loan amount (RMB)	Amount of the loan in RMB
Interest rate (%)	Annual interest rate applied to the loan
Interest rate spread (%)	Annual interest rate minus the corresponding 1 year Shibor
Duration (months)	Maturity of the loan expressed in number of months
On-site verification (Y/N)	A dummy 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
Borrower credit score	Credit Score assigned to the borrower by Renrendai
Proportion of Months Delinquent (%)	The proportion of months, over the loan's life, during which the borrower is delinquent. A borrower is delinquent if she misses or delays the monthly payment of the interest and/or the monthly repayment of the principal
Default (0/1)	A dummy variable that takes the value of 1 if a loan is declared in default and 0 otherwise
B. Borrower Characteristics	
Income (RMB)	Borrower's Monthly Income at the origination of the loan. Renrendai provides this information in brackets, with a total of seven 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 Renminbi
Age	Age of the Borrower at the origination of the loan
College degree (0/1)	A dummy variable that takes the value of 1 if the borrower has at least a college or a higher degree
Male (0/1)	A dummy variable that takes the value of 1 if the borrower is a male
House owner status (0/1/2)	A categorical variable that takes the value of 0 if the borrower does not own a house; a value of 1 if the borrow owns a house but she does not have a mortgage; a value of 2 if the borrower owns a house and has a mortgage
Number of applications since registration	Number of loan applications, at the time of the loan origination, made by the borrower since her registration in Renrendai
C. Lenders Characteristics	
Portfolio size (RMB)	Per loan average size of lenders's porfolio measured in Renminbi
Portfolio size (nr. loans)	Per loan average size of lender's portfolio measured in number of P2P loans
Uplan lending (% of RMB)	Per loan average % of the lenders' portfolios (measured in Renminbi) invested via Uplan
Uplan lending (% of loans made)	Per loan average % of the lenders' portfolios (measured in number of P2P loans) invested via Uplan
Portfolio concentration (HHI)	Per loan average portfolio concentration of the lenders' portfolio. Concentration is measured with a Herfindahl-Hirschman index based

	on the relative proportion of each loan in respect to the total size of the lender's portfolio.
Experience (months since first loan)	Per loan average experience of the lenders. Experienced is measure as a the number of months between the origination of the loan and the first loan made by the lender on Renrendai