Can Technology Undermine Macroprudential Regulation?

Evidence from Peer-to-Peer Credit in China

Fabio Braggion Alberto Manconi Haikun Zhu*

March 2019

Abstract

We study the relationship between FinTech and credit regulation. We exploit the tightening of mortgage LTV caps in various Chinese cities in 2013, and a novel database covering all transactions at RenrenDai, a leading P2P credit platform. P2P loans increase in the affected cities, consistent with borrowers tapping P2P credit to circumvent the regulation. P2P lenders do not adjust their pricing to the influx of new borrowers, although their loans exhibit worse ex-post performance. Symmetric effects are associated with a loosening of LTV caps in 2015. Our test provides evidence on the capacity of P2P credit to undermine credit regulation.

JEL codes: G23; G01; G28.

Keywords: peer-to-peer credit; household leverage; macroprudential regulation; loan-to-value caps; Chinese financial system.

*: Braggion: Tilburg University and CentER, f.braggion@uvt.nl; Manconi: Bocconi University, alberto.manconi@unibocconi.it; Zhu: Erasmus University Rotterdam, h.zhu@ese.eur.nl. Braggion gratefully acknowledges financial support from the NWO VIDI grant, and Zhu from the Institute for New Economic Thinking grant #INO16-00023. We thank Christoph Basten, Christoph Bretsch, Wilko Bolt, Elena Carletti, Fabio Castiglionesi, Joost Driessen, Miguel Ferreira, Rik Frehen, Mariassunta Giannetti, Jasmin Gider, Olena Havrylchyk, Zhiguo He, Tao Li, Nicola Pavanini, Nagpurnanand Prabhala, Enrico Sette, Tao Shu, Zaiyan Wei, Yishay Yafeh, Fabrizio Zilibotti, seminar participants at the Bank of England, Bank of Italy, Bristol University, CUHK, University of Cologne, Dutch Central Planning Bureau, University of Exeter, HKUST, University of Mannheim, NUS, University of Rochester, SMU, St. Louis Fed, and Tilburg University, as well as participants at the ADBI Shenzhen, the 1st COPFIR, the 2018 CREDIT, the 2018 IWFSAS, the Banque de France Digital Finance, CPER Financial Stability and Regulation, Swedish House of Finance Fintech, Cleveland Fed/OFR/University of Maryland Financial Stability and Fintech, Shanghai Fintech, and 2017 SFS Cavalcade Asia-Pacific, and RIDGE Forum conferences for useful comments. All remaining errors are ours.

The global crisis of 2007-2009 has turned the attention of economists and regulators to the relationship between household leverage and macroeconomic performance.[1] The ensuing debate has revolved around how best to contain household debt relying on macroprudential tools, i.e. policies intended to prevent the financial system from generating and/or exacerbating recessions (Hanson, Kashyap, and Stein (2011); Claessens, Gosh, and Mihet (2013); Aikman et al. (2019)). Among those tools, much emphasis has been placed on loan-to-value (LTV) caps, which prevent borrowing beyond a certain fraction of the value of the assets to be purchased with the loan.[2] LTV caps typically target traditional financial intermediaries, such as banks. That, however, might be too narrow if households have access to alternative, lightly regulated credit channels that allow them to circumvent limits on borrowing from regulated lenders. In this paper, we study one emerging – and so far neglected – such channel: peer-to-peer (P2P) credit.

By now rivaling traditional consumer loans in size and reach (Morse (2015)), P2P credit has experienced double-digit growth in developed economies such as the U.S., where lending volumes amounted to $77bn in 2015.[3] The fastest-growing P2P credit market, however, is China, which is also estimated to be the largest in the world (Deer, Mi, and Yuxin (2015)), with volumes totaling over $116bn

[1] There is a vast theoretical and empirical literature on the impact of (household) leverage on consumption, employment and output. Part of the theory contributions stress the role of collateralized lending, with arguments based on Stein (1995) and Kiyotaki and Moore's (1997) works, see e.g. Geanakoplos (2010), Gorton and Ordoñez (2014). Hall (2011) and Guerrieri and Lorenzoni (2017) show that high debt levels can exacerbate downturns even in the absence of collateralized lending. The empirical analyses of Lamont and Stein (1999), Almeida, Campello, Liu (2006), and Baker (2018) show that with high levels of household leverage, income shocks have a strong positive impact on house prices growth. In several studies Adelino, Schoar, and Severino (2012, 2016), Mian and Sufi (2009, 2011), Mian, Sufi, and Trebbi (2015) document the relationship between U.S. household leverage and the severity of the 2007-2009 crisis. Bordo (2008), Claessens, Kose, and Terrones (2012), and Schularick and Taylor (2012) find that crises are typically preceded by periods of rapid credit growth. Mian and Sufi (2010) and Di Maggio and Kermani (2017) document the real economy disruptions associated with high household leverage.

[2] See for instance Allen and Carletti (2011), Crowe, Dell'Arriccia, Igan, and Rabanal (2011), Claessens, Gosh, and Mihet (2013), Jácome and Mitra (2015). Claessens, Gosh, and Mihet (2013) document that LTV-based policies are the most widespread macroprudential tool, both in developed and emerging economies. Out of the 48 countries surveyed in their study, 44% imposed an LTV cap at least once between 2000 and 2010. In contrast, debt-to-income (DTI) caps, the other main macroprudential tool intended to limit household leverage, were applied in only 9% of the countries in their sample.

[3] "As money pours into peer-to-peer lending, some see bubble brewing", *Bloomberg*, May 15, 2015.

(RMB 789bn) as of December 2018, and corresponding to about 20% of consumption loans to households provided by traditional banks.[4]

A P2P credit company acts as a "broker," offering an online platform that brings together borrowers and prospective lenders. To see how P2P credit can act as a channel to elude LTV caps, suppose a borrower intends to take out a mortgage with a bank to purchase a house worth 100. Suppose further that there is a 50% LTV cap on the mortgage, and that the borrower can only commit 40 as a down-payment. Other things equal, the LTV cap rules out the mortgage. If, however, the borrower can obtain an additional credit of 10 on the P2P platform (or if P2P credit helps her free up funds for an amount of 10, which can then be added to her down-payment), the bank can issue the mortgage and the LTV cap is circumvented.

Three features of P2P credit make it especially conducive to this sort of regulatory arbitrage. First, it provides borrowers with a degree of anonymity, since P2P platforms typically impose much more modest disclosure requirements, and receive much less regulatory scrutiny, in comparison to banks and conventional financial intermediaries. In that respect, P2P credit is similar to traditional non-bank sources of credit such as family and friends, payday lenders, etc. Second, and unlike those traditional sources, P2P credit provides access to an unprecedentedly large potential funding pool – in principle, any lender on the platform. Third, P2P credit companies have a lean structure and conduct most of their business online, without physical branches or loan officers. That reduces their costs, and can help them channel, for a given level of borrower risk, cheaper credit. Thus, borrowers can potentially find on a P2P platform anonymous, abundant, and cheap credit that can fund the regulatory arbitrage scheme. Building on these ideas, we assess to what extent P2P credit poses a vulnerability to LTV-based policies and contributes to fueling household debt creation.

[4] "Chinese P2P lending regulations target hucksters and risk-takers", *Financial Times*, August 24, 2016, and WDJZ (https://www.wdjz.com).

Taking this question to the data confronts us with two empirical challenges. First, we are interested in gauging the capacity of P2P credit *supply* to undermine LTV caps. But the equilibrium in the market for loans also depends on credit *demand*; and separating demand and supply is difficult, because the econometrician only observes lending outcomes ex post. An increase in P2P loans, for instance, could be due to inefficient lending induced by excess credit supply, but just as well to improved economic prospects raising credit demand. To separate the effects of P2P credit demand and supply, we need a shock to the demand for P2P credit 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 credit demand and supply can confound the interpretation of any test. Thus, while we study the effects of a change in P2P credit demand, we want to be able to hold the P2P lending supply curve fixed.

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

We study P2P credit around a regulatory change in the Chinese real estate market, which took place in November 2013. The local governments of a number of Chinese cities imposed a 16.7% increase in the minimum down-payment required to obtain a mortgage for the purchase of a second home, raising it from 60% to 70% of the property's value. The objective was to slow down the growth in real estate prices, following a policy impulse in this direction by the Chinese central government (we discuss the background to the regulatory change in detail in Section II.A). Anecdotal evidence, however, suggests that real estate investors circumvented the new requirements, borrowing via P2P credit platforms to meet the increased down-payment.[5] Importantly, the regulatory change created a positive shock to P2P credit demand, thus addressing our first empirical challenge.

We exploit this policy intervention in a difference-in-differences setting, studying changes in P2P credit around this episode, for affected and un-affected cities. We assemble a novel, hand-collected database containing all loan applications and credit outcomes for a leading Chinese P2P credit platform, RenrenDai (人人贷). Our database contains all the transactions executed within the platform, and it matches each borrower with her lenders.

Our results are consistent with P2P lending providing an unregulated source of credit with the potential to undermine LTV caps. In the analysis, we are very careful about identification and what we can and cannot conclude; our baseline effects, however, are already visible in Figure 1, which plots loan application volumes at RenrenDai, for "treated" and "control" cities, around the last quarter of 2013. The lines corresponding to treated and control cities closely overlap over the entire two-year period preceding the regulatory change. Following the last quarter of 2013, however, loan applications in the treated cities increase sharply relative to the control cities, 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 credit in China during our sample period, in the first six months of 2014 applications in the treated cities grow by 50%, as opposed to only 16% in the control cities, consistent with P2P credit being instrumental to circumventing the regulatory LTV cap.

Our formal 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, we leverage the depth of our data with the borrower-lender level regressions, which allow us to trace the

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[5] "China to Crack Down on P2P Lenders," *Financial Times*, March 14, 2016.

impact of the P2P lending demand shock controlling for lender × date fixed effects. These estimates compare the P2P credit received by different borrowers from *the same lender at the same point in time*, thus holding credit supply capacity fixed and addressing our second empirical challenge.

Our estimates imply that the increase in P2P loans we observe accounts for about 70% of the increase in down-payment requirements in the larger "Tier 1" cities like Beijing or Shanghai, and about 50% in "Tier 2" cities like Changsha, Shenyang, or Wuhan. Given that RenrenDai, though an important market player, is but one of a large number of P2P 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 estimates provide a lower bound on the importance of P2P lending as a channel to circumvent regulatory LTV caps. Consistent with this view, to the extent that the goal of the regulator was to reduce house-price levels or at least slow them down, the regulatory intervention itself appears ineffective: house price growth at the treated cities does not slow down relative to the control cities after November 2013.

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 rates of on-site verification for borrowers who obtain a loan after the 2013 episode. In contrast, tighter screening on part of the lenders would predict ex post higher credit scores and higher rates of on-site verification.[6] In addition, we do not detect any significant changes in loan yields or maturities. That is in spite of the fact that default rates increase, by about 30% relative to their pre-2013 levels. These results suggest that lenders on the RenrenDai platform have an "inflexible" lending technology, which does not allow them to adjust their lending decisions, even though they are making loans that turn out to be riskier.

[6] We treat both the credit scoring system and the on-site verification as screening devices available to lenders. In principle, on-site verification is a *signaling* tool available to the *borrowers*, whereby more creditworthy borrowers may choose to have their information directly verified by the platform. But if lenders tighten their screening, they are less likely to make loans to borrowers who are not on-site verified; in that sense the ex post rates of on-site verification reflect screening.

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

Our findings make three main contributions. First, we contribute to the growing literature that studies the relationship between new financial technologies and credit regulation (e.g. Buchak et al. (2018), de Roure, Pelizzon, and Thakor (2018)). One could view FinTech as a source of shadow banking, with the potential to pose risks to financial stability (Tarullo (2019)). Our evidence indicates that P2P credit can be a vehicle for regulatory arbitrage; and regulatory arbitrage has long been considered one of the main drivers of the growth of shadow banking. Interestingly, however, a large part of the literature has focused on the elusion of regulatory constraints by financial intermediaries such as banks or other lenders, i.e. on the side of credit *supply* (Adrian and Ashcraft (2012), Buchak et al. (2018), Plantin (2014)). Our results point to the fact that regulatory arbitrage on the side of credit *demand* (enabled or facilitated by the presence of the more lightly regulated P2P channel) can also be economically very relevant.

Second, our paper contributes to the literature on the drivers of household leverage. Financial (il)literacy (Lusardi and Tufano (2009)), real estate prices (Mian and Sufi (2011), Crowe and Ramcharan (2013)), and import competition (Barrot et al. (2017)) have been found to be important factors behind household debt. Our findings suggest a new, and so far neglected factor: The development of financial technology and the disintermediation of financial services.

Third, our test speaks to the ongoing debate on the systemic impact of household leverage, and on the design of policies to contain it. 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 2007-2009 crisis (Mian and Sufi (2009), Claessens et al. (2010)). A second view focuses on credit demand, on the grounds that household leverage growth encompassed not only lower-income borrowers, but also the middle-class ((Adelino, Schoar, and Severino (2012, 2016), Foote, Gerardi, and Willen (2012), Foote, Loewenstein, and Willen (2016), Albanesi, De Giorgi, and Nosal (2017)). Our findings present fresh evidence from a different context – China – and time period – 2010-2017 – and highlight the role of both credit demand (to meet the down-payment requirements) and credit supply (from P2P lending). They also point to a vulnerability of LTV caps, a central instrument in the macroprudential toolkit (Allen and Carletti (2011), Crowe et al. (2011), Claessens, Gosh, and Mihet (2013), Jácome and Mitra (2015)). A potential solution would be to monitor other indicators than LTV (for example, debt-to-income ratios), as well as the borrowers' overall indebtedness. The risk, however, is to throw out the baby with the bathwater, losing the flexibility that makes P2P credit a viable business in the first place.

The remainder of the paper is organized as follows. Section II provides the institutional background and lays out our empirical predictions with the aid of a simple model. Section III presents our data and identification strategy. Section IV reports our baseline findings on changes in P2P lending volumes around the 2013 tightening of LTV caps, and Section V on subsequent changes in loan screening, pricing, and performance. Section VI presents similar tests around the 2015 LTV cap relaxation. Section VII discusses the policy implications of our findings. Section VIII concludes.

II. Background and predicted impact of the change in LTV caps

A. Background

Most of the analysis in our paper revolves around a regulatory change in the Chinese real estate market, which took place in November 2013. Since about 2011, China had experienced strong growth in real estate prices. Over the period 2012Q4-2013Q4, the *100-City Price Index*, a broad index of house prices published by the China Index Academy (中国指数研究院), rose by 14%; and among the cities with over 5 million inhabitants comprised in our sample, the mean increase in house prices was 11%, and the largest increase over 78%. In comparison, the inflation rate over that period was about a mere 2.6%.

In response to the perceived overheating of the real estate market, the General Office of the State Council issued on 26 March 2013 a "Notice on Further Improving Regulation of the Real Estate Market" (国务院办公厅关于继续做好房地产市场调控工作的通知) instructing local regulators to contain house prices.[7] Historically, Chinese authorities had pursued the objective of house prices moderation with two main levers: taxation on house sales and limits to house purchases.[8] The notice called for a stricter enforcement of those policy tools, which were in fact already in place in a number of cities. In addition, for the first time in an official regulatory communication since 2011, it raised the possibility of an increase in minimum down-payment requirements on home mortgages. The increase was not mandated, but rather the notice left it up to provincial and city governments whether to undertake it or not (we return to this point in Section VII). Conditional on a decision to tighten down-payment requirements, the implementation and enforcement of the regulation was delegated to local branches of the People's Bank of China.[9]

Following the publication of the notice, regulators in Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenzhen, Shenyang, and Wuhan imposed a 16.7% increase on the minimum down-payment required to obtain a mortgage for the purchase of a second home, raising it

[7] The notice was addressed to provincial governments, ministries and commissions of the State Council, and other directly affiliated institutions, as well as city governments, ministries, commissions, and affiliated institutions at the local level. Also see "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.
[8] As of 2013, 31 major cities in China with population over 5 million imposed a limit on the number of homes that a given household or individual could own.
[9] Unlike the central banks of other major economies, the People's Bank of China is actually a department of the State Council. It (or its branches) may thus implement policies determined by the administrative authorities, such as the provincial and city governments in this case.

from 60% to 70% of the property's value. The stated objective of the intervention was to slow down the growth in real estate prices.[10] As we mentioned, anecdotal evidence suggests that real estate investors circumvented the new requirements, borrowing via P2P credit platforms to meet the increased down-payment.[11] Our main tests take this notion to the data, and examine its implications for the relationship between P2P credit and macroprudential regulation.

In a further set of tests, we also look at a symmetric change in regulation, which took place in September 2015. During 2015, the Chinese economy experienced a significant slowdown. In March, the government cut its GDP growth target to 7% – down from an earlier target of 8%, as well as from growth rates averaging over 10% in the previous 5 years. To cushion the effects of slower growth, a broad stimulus package was launched, which included measures to support the housing market. In September, the General Office of the State Council released a "Notice of the People's Bank of China and the China Banking Regulatory Commission on Issues concerning Further Improving the Differential Housing Credit Policies" (中国人民银行中国银行业监督管理委员会关于进一步完善差别化住房信贷政策有关问题的通知), instructing all Chinese cities with the exceptions of Beijing, Guangzhou, Sanya, Shanghai, and Shenzhen to relax minimum down-payment requirements on the purchase of a first home by 16.7%, bringing them down from 30% to 25% of the property's value. In February 2016, in the same set of cities, down-payment requirements on first homes were further reduced by 5 percentage points, and the relaxation of LTV ratios was also extended to mortgages for the purchase of a second home.

B. Predicted impact of the change in LTV caps

[10] "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. Most cities increased mortgage down-payment requirements in November, with the only exception of Beijing, which increased them in May. For that reason, the visual analysis of Figure 1 is focused on the last quarter of 2013. In the tests discussed below, however, Beijing is considered a treated city starting in the second quarter of 2013.

[11] "China to Crack Down on P2P Lenders," *Financial Times*, March 14, 2016.

To analyze the impact of P2P credit on the effects of changes in regulatory LTV caps (mortgage down-payment requirements), we rely on a 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 tightened LTV cap, sterilizing its effects such that the levels of new credit are not reduced. These results allow us to formulate the key empirical predictions for our test.

First, we consider an economy populated by households (borrowers) and competitive traditional, regulated lenders ("banks"). At a later stage, we introduce unregulated ("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 the 2013 tightening of the LTV cap as an increase in δ, and study its effects on the total amount of debt promised interest payments level, and default rates 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 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, representing 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 $y = d_b + d_l$, where d_l is her payment to the bank and d_b is the portion of cash flow she retains. If the borrower defaults, the bank recovers a value

$R < I$ (e.g. as the result of a foreclosure process).[12] R is exogenously given.[13] 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:

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

Since banks are competitive, (1) 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:

$$d_b \geq B/\Delta_p. \tag{2}$$

Combining (1) and (2) with the resource constraint $y = d_l + d_b$, as long as $y \geq B/\Delta_p + d_l$ we have the following condition for the bank to make a loan:

$$A \geq \bar{A} = I - p_H\left[y - \frac{B}{\Delta_p} + (1 - p_H)\frac{R}{p_h}\right] \tag{3}$$

Expression (3) implies that only borrowers with sufficiently high assets-in-place (i.e. able to meet the down-payment requirements) obtain credit.

To analyze the 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 (1) we have:

$$i_l = \frac{1}{p_H}\left[1 - \frac{R(1-p_H)}{I-\bar{A}}\right] - 1 \tag{4}$$

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

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[12] 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.

[13] 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 growth).

Consider now the effects of an LTV cap tightening, 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 (in the language of Holmstrom and Tirole (1997), this is equivalent to a "collateral squeeze"). 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 new LTV cap curbs the level of debt in the economy. Because the bank has a smaller exposure to each borrower, moreover, interest rates decrease via expression (4), 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: tightening the LTV cap reduces new credit, as well as aggregate interest payments and defaults.

Suppose next that an additional set of lenders is introduced, which we refer to as the P2P lenders. Unlike the banks, P2P lenders are not subject to regulation enforcing a minimum down-payment requirement on their loans. Moreover, the P2P lenders are assumed to be competitive and "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)), as well as what we find in our data (discussed in the next section). A simple strategy for a 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. We study whether this strategy can be sustained in equilibrium, and its implications.

In addition to being unregulated, the P2P lenders differ from banks in two main respects. First, they 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:

$$p_H d_{P2P} \geq \bar{A} + \delta - A, \tag{5}$$

where the P2P lenders' payoff is scaled by p_H because the borrower also receives credit from the bank, which already provides the incentive to exert effort.[14]

A sufficiently large y ensure that in equilibrium borrowers turn to the bank first, and if they do not have sufficient assets-in-place they also borrow from the P2P lenders to meet the down-payment requirement. Because the P2P lenders are competitive, the P2P participation constraint (5) holds with equality, and $d_{P2P} = (\bar{A} + \delta - A)/p_H$. The participation constraint for the bank (1) 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 endogenous minimum level of assets-in-place $\bar{A}$ required to obtain credit from the bank is 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 (3). In other words, regardless of the size of the increase in the down-payment requirement δ, an identical mass $1 - G(\bar{A})$ of borrowers obtains credit, and the total level of debt in the economy is unchanged. Also note that for any size of the loan, P2P credit is more expensive, because the bank is collateralized. The interest rate demanded by the P2P lenders, implied by (5), is: $i_{P2P} = \frac{1}{p_H} - 1$, which is larger than $i_l = \frac{1}{p_H}\left[1 - \frac{R(1-p_H)}{I-(\bar{A}+\delta)}\right] - 1$, so that indeed a given borrower will only turn to the P2P lenders if she cannot meet the down-payment requirement. In sum: the objective of the tightened LTV cap is to curb new credit. The availability of P2P credit, however, sterilizes the cap, leaving new credit unchanged.

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

[14] 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.

2013 increase in down-payment requirements, we will observe a larger volume of new P2P loans in cities that raise mortgage down-payment requirements (treatment group) than in other cities (control group). The effect will be the opposite around the 2015 relaxation of down-payment requirements.[15]

II. Data and identification

A. Data

We base our analysis on a large, loan- and loan application-level database from a leading Chinese online P2P credit platform, RenrenDai (人人贷). RenrenDai was launched in 2010, and quickly developed into one of the main players in the Chinese P2P credit sector, with cumulative turnover of RMB 25bn ($3.7bn, as of February 2017) and close to 4 million registered accounts (2017 1st quarter). Among the over 2,000 Chinese P2P credit platforms active as of December 2016, RenrenDai ranks, by turnover, in the top 1%. Our database spans the period from October 2010, when RenrenDai first opens to the public, until February 2017. In total, the data contain 955,174 loan applications, made by 746,647 individual borrowers, and involving 351,333 lenders.

Table 1 reports summary statistics for our data, over a window of 37 (–18, +18) months around the 2013 mortgage LTV cap tightening (May 2012-May 2015). The average loan has a size of RMB 59,674 ($8,840), with an annualized interest rate of 12.5% and duration 27 months. The average RenrenDai borrower has a pre-tax monthly income of RMB 11,334 ($1,679), or about RMB 136,000

[15] 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 interest payments remain unchanged after the increase in down-payment requirements, because $\frac{\partial}{\partial \delta}(d_l + d_{P2P}) = 0$. Similarly, aggregate defaults are unaffected by down-payment requirement and remain equal to $(1 - p_H)[1 - G(\bar{A})]$, because individual borrower default risk depends on the realization of future cash flows Y. In particular, in this framework a default on the bank loan also implies a default on the P2P loan as the borrower's cash flows are 0; but in practice mortgage maturities tend to be considerably longer than the average duration of a P2P loan (2-3 years in our data, Table 1). A more flexible model might incorporate that feature; it might also generate increasing default rates as borrowers turn to P2P lending (consistent with the evidence we discuss in section V). We feel that such a model is beyond the scope of our study, as our focus is mainly empirical.

($20,148) yearly. Based on data from the China Household Finance Survey, the mean after-tax yearly income for Chinese individuals with outstanding debt, living in non-rural areas in the provinces where RenrenDai is active, is RMB 74,000 ($10,963).[16] With an average income tax rate of about 40%,[17] therefore, RenrenDai borrowers appear in line with the population average. The loan face value is typically 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 and 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" (50%), "Consumption/General" (14.3%), and "Entrepreneurship" (11.4%). The data also report each borrower's credit score, based on RenrenDai's internal scoring system. There appears to be relatively 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, in addition to her income level we are able to observe a number of characteristics, including demographics such as gender, age, city of residence, etc. Additional data items are disclosed by the borrowers on a voluntary basis, such as 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 (2017)), the median RenrenDai borrower is a home owner.[18] 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 at

[16] The China Household Finance Survey is administered by the Southwestern University of Finance and Economics. The data are based on the 2011 wave of the survey (the only one available at the time of writing).

[17] Income taxes are progressive in China (cf. e.g. https://www.ecovis.com/focus-china/individual-income-tax-iit-china-ground-rules/). The 40% average tax rate is based on a back-of-the-envelope calculation for an individual with a pre-tax income of RMB 130,000 as in our data.

[18] This value refers to the entire May 2012-May 2015 period. Table 2, where the data are restricted to the period prior to November 2013, reports a lower value. That is consistent with an influx of borrowers who are home owners in the period subsequent to November 2013, as we discuss below.

least some of 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 credit data (e.g. Balyuk (2017), Morse (2015)), we are not able to directly observe lender characteristics, but we can characterize them by looking at the features of the lenders' loan portfolios. In Table 1.C, we report the characteristics of the average lender on a given loan (the mean number of lenders per loan is 45; median: 30). On average, lenders hold a portfolio of 235 loans, with a total face value of RMB 387,978 ($57,478). Income per capita in China in 2013 was $7.077; in Beijing and Shanghai, the two largest cities in the country, it was $15,143 and $14,560 respectively.[19] Thus, the average lender's investment is between 4 and 8 times per capita income; that is consistent with anecdotal and survey evidence indicating that investors on RenrenDai are households belonging to the emerging Chinese middle class (Deer, Mi, and Yuxin (2015)). The average lender has an experience on RenrenDai of about 7 months. Finally, lenders can choose to make their loans directly to borrowers, or delegate the allocation of their funds across different loans to automatic investment plans, based on a "robo-advisor" technology that matches lenders to borrowers mostly based on returns and maturity preference parameters set by the lender. The main automatic investment plan on RenrenDai is called Uplan (U 计划), and around 70% of all loans are made through it.

B. Identification approach

The structure of our data helps 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 control for unobserved lender heterogeneity and hold credit supply fixed with a fixed effects strategy. Intuitively, our test compares two loans, made by the *same P2P lender, at the same point in time,* to two different borrowers, Fang and Wei. Fang is

[19] Source: World Bank National Accounts Data.

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 the lender, 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.[20]

We analyze changes in P2P loans, comparing affected and un-affected real estate markets around the 2013 and 2015 changes in minimum mortgage down-payment requirements described above. The baseline test takes the form of a difference-in-differences regression:

$$L_{blt} = \alpha + \beta Treated_{bt} + \gamma Post_t + \delta(Treated_{bt} \times Post_t) + \mu' x_{blt} + \varepsilon_{blt} \tag{7}$$

where L_{blt} denotes a loan 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 then take first differences, estimating:

$$\Delta L_{bl} = \alpha + \delta Treated_{bt} + \mu' \Delta x_{bl} + \eta_{bl} \tag{7'}$$

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

Given the features of the data at our disposal, we can estimate model (7)-(7') on different levels of granularity, allowing to control for alternative potential confounding factors. In the simplest

[20] 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); Chodorow-Reich (2014)). 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.

specification, we estimate equation (7') on the city-date level data, i.e. studying the behavior of all loans (applications) in a given city at a given point in time around each change in down-payment requirements.

In a second specification, we estimate model (7) on the individual loan-lender level, i.e. where each observation corresponds to a borrower-lender pair, that is 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 (this is equivalent to including lender fixed effects in equation (7')).

The nature of the experiment also helps us with identification. As the 2013 changes of LTV caps pertained only the purchase of second homes, we should find that our results are driven by P2P borrowers that are homeowners, a conjecture that we verify in our tests.

C. Comparison of treatment and control groups prior to November 2013

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), and overall make up about 22% of the population of urban China.[21] In addition, the treatment affects both "Tier 1" (Beijing, Guangzhou, Shanghai, and Shenzhen) and "Tier 2" (Changsha, Hangzhou, Nanjing, Shenyang, and Wuhan) cities. We take all other Chinese cities with active borrowers on RenrenDai and population over 5 million as our control group; the overall sample comprises 52 cities, with an aggregate population of 431 million; in those cities are located 56,254 RenrenDai borrowers as of November 2013, corresponding to 63% of the platform's active borrowers.

In Table 2, we compare the loans associated with the treatment and control cities along observable dimensions, prior to November 2013. Panel A focuses on borrowers. Borrowers from treated and control

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

cities do not exhibit significant differences in terms of monthly income (RMB 11,216 and 11,873 on average), age (about 39 for both groups), 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 for the difference: 1.69), and less likely to be home owners (18%, compared to 27% for the control group; t-stat: -2.04).[22] 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. Finally, in Panel C the treated and control cities are compared in terms of macroeconomic variables. We detect no significant differences along the dimensions of per capita GDP (level and growth), population (level and growth), household net debt to income, real wages, house price index and RenrenDai penetration rates.

In sum, we do not observe large differences along observable dimensions between the 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.

IV. Baseline tests

A. City-level estimates

We run a first set of regressions on city-level data. We estimate model (7') by time-averaging, collapsing the data, and taking first differences, as described above, to control for serial correlation in the standard errors (Bertrand, Duflo, and Mullainathan (2004)). The results are reported in Table 3. The estimates in Table 3.A support the evidence from Figure 1, as well as the arguments illustrated in Section II. They

[22] These values are based on observations prior to November 2013, explaining the difference from the average home ownership rates in Table 1, which are based on the entire sample.

imply that, over the 18-month period following the 2013 rise in down-payment requirements, loan applications in the treated cities increase by about 112% (= 0.062×18, specification (2)), and the RMB volume of actual P2P loans by 56% (= 0.031×18, specification (4)), both of which appear economically substantial.

Separate tests also show that house price growth does not slow down in the treated cities – despite the fact that that was precisely the aim of the regulatory intervention. The estimates, reported in columns (5) and (6), have specification analogous to columns (1)-(4), but the dependent variable is now the monthly change in house prices in a given city. The implied effects are near zero; in fact, in specification (6) we observe a positive and significant coefficient on the $Treated$ indicator, implying an increase in house price growth in the treated cities relative to the control cities (economically, however, the difference is modest, at 0.3 percentage points per month, and not statistically significant). In sum, it appears that the rise in down-payment requirements was largely ineffective in slowing down house price growth at the treated cities.

As a final check, we visually inspect the time series of traditional bank lending at the treated and control cities in Figure 2.[23] Over the period 2009-2015, the volumes of credit at the two groups of cities move in parallel; in particular, we do not detect any deviation from the pre-2013 trend at the treated cities, relative to the control cities, around 2013. Moreover, Figure 2 does not indicate a generalized growth of credit at the treated cities over and above the control cities; that suggests that the effect that we capture is specific to P2P credit, and does not manifest itself in other sources of credit.

B. Loan-level estimates

[23] Traditional bank lending equals the total amount of credit extended by Chinese banks over our sample period. Detailed data on the separate components of bank credit (e.g. mortgages, consumer credit, credit to businesses) on a province or city level are, to the best of our knowledge, not available.

The city-level evidence is consistent with the notion that borrowers use P2P lending to circumvent the increase in down-payment requirements. A rise in P2P loans, however, can be in general the result of a combination of shifts of the credit demand and credit supply curves. 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 observe in Table 3. To control for credit supply side effects, we estimate model (1) on data matching individual lenders and borrowers, controlling for lender $\times$ 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 $\times$ date fixed effects; specification (4) reports the corresponding estimates without them. Overall, the estimates are in line with those of Table 3, and consistent with an increase in P2P lending demand to circumvent the down-payment requirement increase. Economically, the effects are also meaningful. The estimation window employed in the tests of Table 4.A covers a 3-year period ($\pm$18 months) around the 2013 increase in down-payment requirements, from May 2012 until May 2015. The estimates are based on monthly data, and they imply a 2.3-4.5% monthly increase in P2P borrow at the treated cities, relative to the control cities. Taking the 3.4% midpoint of that range, over the 18-month period following November 2013 that implies approximately a 60% increase in P2P loans. Compared to the average loan size of about RMB 60,000 (about $8,888), this roughly corresponds to a RMB 36,000 increase.

The value of a medium-size apartment (70 sq. meters) in 2013 in Nanjing (the median among our treatment group cities in terms of house prices) is RMB 875,000 (about $129,630), so that the increase we document accounts for 41% (= RMB 36,000 / RMB 87,500) of the 10-percentage point increase in down-payment requirements. Across the set of treated cities, the effects implied by the estimates of Table 4.A account for between 19% (relative to Beijing house prices) and 81% (Changsha house prices) of the increase in down-payment requirements.[24] 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 likely provide a lower bound on the importance of P2P lending as a channel to circumvent the new requirement.

We also separately analyze the intensive margin (whether repeat borrowers increase their borrowing on RenrenDai after November 2013) and the extensive margin (whether one-time borrowers are more likely to turn to RenrenDai, or borrow larger amounts, 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 0.008, statistically indistinguishable from zero; the corresponding estimate in the extensive margin regression is 0.034 (t-stat: 2.61). The difference between the two coefficients is close to the estimated coefficient on $Treated$ in specifications (1)-(4), suggesting that the effect is driven by the *extensive* margin: in other words, an influx of one-time borrowers after the 2013 increase in down-payment requirements explains our baseline effect.

These results are robust to a number of checks, summarized in Table 4.B. First, we split the treatment group, separating Tier 1 cities (Beijing, Guangzhou, Shanghai, and Shenzhen) and Tier 2 cities (all other cities), based on an informal hierarchy popularized in the media. Tier 1 cities are larger, richer, and typically more expensive. When we estimate a modified version of equation (7)-(7') on the two groups, we find a coefficient of 0.117 on the Tier 1 cities, three times larger than the baseline of Table 4.A, and a coefficient of 0.024 on the Tier 2 cities, somewhat smaller than the baseline. These estimates

[24] We obtain city-level data on house prices per square meter from the databank of China Index Academy, a leading real estate research organization in China.

bring the economic effects in larger and smaller cities closer to each other, accounting for about 70% of the implied increase in down-payment requirements in Beijing or Shanghai and about 50% in Changsha, Shenyang, and Wuhan. Second, we also find similar effects, economically stronger than the baseline of Table 3.A, if we restrict the sample to loans made by lenders who were active on the RenrenDai platform prior to November 2013, either as registered users (specification (3)) or by having made a loan (specification (4)). This restriction ensures a homogeneous set of lenders before and after November 2013. Our regressions already control for lender $\times$ date fixed effects, and the restriction further attenuates potential concerns about a correlation between changes in the composition of credit supply and changes in credit demand around the regulatory intervention. Finally, we find similar effects as in the baseline estimates if we include in the regression specification an additional set of city-level controls, such as city GPD per capita and population levels and growth rates (specification (5)), as well as if we estimate a specification in which not only the $Treated$ indicator, but all other control variables are also interacted with the $Post$ indicator (specification (6)).

C. Further tests: Borrower and lender characteristics

Further analysis provides a richer characterization of these findings. First, in Table 5 we partition the sample based on borrower characteristics. We document that the increase in P2P borrowing at the treated cities is driven by loans to home owners (specifications (1)-(2)). This is consistent with the fact that the LTV cap tightening only affects second-home mortgages. The implied economic effects are also larger in this case, accounting for 64% of the required additional down-payment in Nanjing, the median treated city in terms of house prices. We also consider expected house prices growth rates after November 2013 as a mediator.[25] We find that our baseline effect is stronger among treated cities where the expected

[25] We compute expected house price growth rates based on the predicted values based on an AR(1) process for city-level house prices, estimated on monthly data, controlling for previous month interest rate, and macro/demographic variables such as city population, net debt per capita and development in real estate (number of new houses).

house price growth after November 2013 is above the median (specifications (3)-(4)). That is consistent with the notion that borrowers need larger loans to meet down-payment requirements on larger mortgages. It is also consistent with a speculative motive behind the regulatory arbitrage: borrowers attempt to circumvent the LTV tightening where they expect a higher return on real estate investment.[26]

Second, in Table 6 we partition the sample based on lender characteristics: lending via Uplan or direct lending, experience, and portfolio size. Specifications (1) and (2) shows that our effect is mainly associated with lenders who make loans as part of Uplan, which account for the majority of loans in our data (specifications (1)-(2)).[27] Moreover, borrowers in the treated cities receive financing from lenders regardless of the level experience: in both specifications (3) and (4), the coefficient on $Treated$ is positive and statistically significant. The estimated effect is, in fact, slightly larger in magnitude for lenders with above-median experience (although the difference is not different from 0 at conventional levels of statistical significance). Having a longer experience on RenrenDai as a lender, apparently, is no obstacle to increasing lending at the treated cities. Finally, specifications (5)-(6) distinguish lenders based on their portfolio size. The coefficients on $Treated$ is positive and significantly different from zero both for lenders with below and above median portfolio size. The coefficient in the subsample of lenders with large portfolios is larger (0.033 as opposed to 0.022; the difference is statistically significant, with p-value 0.02). That suggests that the increase in P2P lending at the treated cities after November 2013 is driven primarily by larger lenders. To the extent that lenders with larger loan portfolios are likely

[26] The control group observations in the estimates of Table 5 are the same across specifications (1)-(2) and (3)-(4), whereas we split the treatment group. Intuitively, in this way we capture increases in P2P credit that take place both on the extensive margin (e.g., more home-owners borrow in the treated cities) and the intensive margin (e.g., home-owners demand larger loans in the treated cities).

[27] There does not appear, however, to be any form of specialization of Uplan loans towards the treated cities. In fact, the proportion of loans to borrowers located in the treated cities made via Uplan or direct lending is nearly identical: 31% (Uplan) and 32% (direct lending), in terms of the number of loans, and 32% via both channels in RMB terms. The effect is driven by loans made via Uplan simply because Uplan accounts for a large component of the loans made on the platform (around 70%).

financially more sophisticated, it appears that such sophistication does not prevent them from increasing lending at the treated cities.[28]

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 II. P2P lenders are able to supply an economically substantial amount of credit, based on the effects discussed above. The expansion of P2P credit is driven by borrowers from cities where faster house prices growth is expected, as well as by a broad range of lenders. In particular, delegating portfolio choice to the Uplan "robo-advisor", longer experience, or greater sophistication do not appear to make lenders less likely to fuel the increased P2P lending.[29]

V. Other loan features; loan performance

The influx of P2P borrowers at the treated cities, and the fact that even experienced and sophisticated investors appear prone to fueling it, raise the possibility of an increased risk exposure for P2P lenders. We now study if the lenders protect themselves against that risk by adjusting loan contract terms, as well as the ex-post performance of their loans.

A. Screening, pricing, and duration of loans

[28] At the same time, even lenders in the largest portfolio size quartile do not appear to have especially large amounts invested via RenrenDai. The average portfolio size in that quartile is about RMB 530,000 ($78,518), and the largest portfolio in our sample has size about RMB 4,100,000 ($607,407), consistent with the view that we are looking at individual lenders (rather than e.g. institutions), as we remarked above. Moreover, and similarly to the remarks we made about loans made via Uplan as opposed to direct lending, there does not seem to be a specialization of lenders with large portfolios towards the treated cities: 32% of their loans go to borrowers located in the treated cities, and a nearly identical fraction for the lenders with smaller portfolios.

[29] Throughout our analysis we implicitly assume that borrowers use P2P funds to purchase a home 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, working against our test and suggesting that our estimates represent a lower bound of the effects of interest. In addition, every city in our treated group has home purchase restrictions in place that actually prevent residents from other cities to purchase a second home in the areas under their jurisdiction. For instance, only a registered resident in Shenzen is allowed to buy a second home 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.

At the same time as they fund P2P loans that, as we documented, are consistent with regulatory arbitrage, RenrenDai lenders can in principle limit their risk exposure by adjusting the features of the loans in which they invest. We consider three central loan contract features: the degree of screening to which the borrower is subject, pricing, and duration.

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 submit to on-site verification, where an officer from You Zhong Xin Ye Financial Information Services Ltd. (友众信业金融信息服务(上海)有限公司), a sister company of RenrenDai, verifies that the information they provided is true by visiting them at their stated address. If lenders respond to the influx of new borrowers by stepping up screening and tightening their lending standards, they may be willing to invest in a given loan only if the borrower has been on-site verified. 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 a change in on-site verification rates in Table 7 (in fact, we observe a slight, although statistically insignificant, decrease in specification (1)).

By a similar logic, tighter screening predicts ex post higher borrower credit scores on the loans. There is no centralized credit bureau in China, and no consumer credit score equivalent to and/or with similar broad coverage as a FICO score. For that reason, a number of Chinese P2P platforms, including RenrenDai, have developed their own credit scoring systems, which are visible to the lenders, as an aid in their portfolio allocation decisions. Our estimates of specification (2) of Table 7 provide little evidence of an increased borrower credit score. That has two possible interpretations: (a) Lenders do not align their investments more closely with credit scores after November 2013, or (b) RenrenDai's credit score is uninformative. Neither interpretation suggests tighter screening. Taken together, these results indicate that the lenders simply do not become more discriminating after November 2013.

In line with these findings, the pricing and duration of loan contracts issued after 2013 also do not change appreciably. We find no significant changes in yield spreads (specifications (5)-(6)), nor in duration (specifications (7)-(8)), after 2013. In sum, P2P lenders treat the influx of borrowers from the treated cities just like their old borrowers, and lend to them at 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 four measures of loan performance: delinquencies (the proportion of months during which the borrower is delinquent over the loan's life), loan default (an indicator equal to 1 if a given loan experiences a default), the log-RMB amount of a defaulted loan, and the log-RMB outstanding amount of the loan at the time of default. When looking at delinquencies and default indicators, the sample size shrinks because of a truncation problem: for some ongoing loans, default may simply not have been declared yet. When looking at the log-RMB measures of on the size of the default, the sample shrinks further, as it is restricted to defaulted loans.[30]

The evidence, reported in Table 8, indicates a deteriorating loan performance at the treated cities following 2013. Delinquencies increase by 1.1 percentage points (specification (1)), and defaults by 0.6 percentage points (specification (2)), relative to the control cities. Similar to the estimates reported by Morse (2015) for the U.S., default rates are on average 2% among RenrenDai loans (Table 1).[31] Our

[30] One caveat is that, to the best of our knowledge, no information on the recovery rates for defaulted loans on RenrenDai is publicly available. Because we cannot account for recovery, therefore, our estimates can be interpreted as an upper bound on the economic loss associated with the defaults.

[31] 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. Below

estimates imply, therefore, that default frequency increases by 30% in relative terms, which appears economically substantial. The losses imposed on lenders also appear to concentrate on the largest loans: the estimates of specification (3) indicate that the defaulted loans are 3.6 times larger at the treated cities than at the control cities. Finally, specification (4) indicates that the RMB size of the default (the part of the loan that does not get repaid) is nearly 30% larger.

Taken together, the evidence presented in this section and the previous one indicates that: (i) Following the 2013 tightening of LTV caps, 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. This suggests that the "lending technology" of the RenrenDai lenders is not flexible enough to induce them to tighten their lending standards in response to the influx of borrowers in the treated cities after November 2013, even though the loans they make turn out to be riskier.

VI. Evidence on the 2015 episode

As explained, in September 2015 a reverse policy intervention was implemented across the country. As part of a broader stimulus package, minimum down-payment requirements on first homes were 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 II, this should curb the demand for P2P lending. In February 2016, in the same set of cities, the minimum down-payment requirement was further reduced by 5 percentage points on first homes, and the LTV relaxation was also extended to second homes.

One caveat to correctly interpret the tests we are about to present is that the demand for P2P lending is expected to decrease, under the assumption that the existing overall credit demand as of

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we discuss an additional test, centered around a similar LTV cap change in September 2015; we discuss the possible impact of the 2015 default wave on that test in the next Section.

September 2015 incorporates a component of borrowers who resort to P2P credit to meet existing down-payment requirements. That appears plausible, based on our findings on the effects of the 2013 policy intervention discussed in the preceding sections.

With that caveat 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 9.A. 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 reduced their reliance on P2P credit, and in particular one-time borrowers obtain smaller loans at the treated cities. 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 9.B. Once again, we do not observe large changes in screening: the coefficient estimate in specification (1) focusing on on-site verification is economically small at negative 6.5 percentage points and not statistically significant; we also do not find any significant changes in credit scores, and the magnitude of the coefficient estimate in specification (2) 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 yield spread of nearly 8%; loan duration drops by about 6%, or just over 1.5 months compared to the sample average of 27 months. Taken together, these findings, as well as those of Sections IV and V, suggest that P2P lenders are generally unresponsive to changes in mortgage LTV caps (and potentially policy interventions in the credit market in general), i.e. they do not condition their lending decisions to the expected "type" of borrower they may face. That is perhaps consistent with the lower sophistication anecdotally associated with P2P lenders, although as we documented RenrenDai lenders have relatively large loan portfolios, suggesting at least some degree of financial sophistication. On the other hand, this evidence indicates that the benefits of P2P credit in terms of informal contracting and "proximate knowledge" found by the earlier literature may be limited in this context.

Finally, when looking at loan performance we observe effects consistent with the ones documented after the 2013 LTV-cap tightening, but with limited statistical significance (Table 9.C). Delinquency rates do not decline (nor increase); default rates decline by 1.1 percentage points; defaulted loans are 12% smaller at the treated cities (but the difference is not significantly different from zero), and the portion of the loan that does not get repaid is 9% smaller. One caveat, as before, is that these results are subject to a truncation problem, as a nontrivial part of the loans in the sample are still outstanding at the time we run our tests. Collectively, these findings are consistent with the interpretation that the relaxation of the LTV cap at the treated cities reduces the incentive to borrow on the P2P platform.[32]

VII. Discussion and policy implications

In light of the evidence reported in the previous sections, we now discuss (1) the design of our test, and (2) the policy implications of our results. Regarding the design of our test, one potential question is why in November 2013 the local governments of the treated cities, but not those of the control cities, decided to tighten mortgage down-payment requirements. As we mentioned, the regulatory change was a response to a rise in real estate prices. But house prices were rising across the entire China, not just the treated cities: in the 6-month period leading to November 2013, house prices relative to per capita

[32] A potential additional issue is the wave of defaults on P2P loans mentioned in the previous section. If the wave affected disproportionately the treated cities vis-à-vis the control cities, it could spuriously induce some of these results. However, a comparison of defaults at the treated and control cities prior to September 2015 reveals, if anything, the opposite: the rate of defaults is 1.9% in the treated cities, and 3.6% in the control cities, and the proportion of delinquent months is 4.6% in the treated cities and 6% in the control cities. This suggests that it is unlikely that our findings are induced by the 2015 wave of defaults.

incomes rose on average by 17.67% in the treated cities, and by 17.62% in the control cities (all non-treated Chinese cities with over 5 million inhabitants in 2013, Table 2).

The combined evidence of Figures 1 and 2 and Table 2 indicates that, prior to November 2013, the treated and control cities were on parallel trends in terms of traditional and P2P credit, and that they did not exhibit significant differences in terms of an extensive list of observable economically relevant variables. That, combined with the fine mesh of fixed effects employed in our tests, considerably raises the bar for any alternative interpretation of our results based on some omitted factor driving systematic differences between treatment and control cities. Given similar ex ante conditions and a similar recent rise in real estate prices, then, why were the policy choices different in those two groups?

We do not pretend to have an exhaustive explanation of the policy choices of local governments in the period surrounding November 2013. Having said that, anecdotal evidence provides some indication as to the factors influencing regulators. Although the General Office of the State Council notice of March 2013 did indicate to the local authorities that they should slow down the growth in real estate prices, as we discussed there was no official mandate to prefer targeting LTV caps over the existing levers of sales taxes and regulatory limits to house purchases. That left local authorities some leeway in defining whether and how to intervene. Anecdotal evidence, as well as a growing empirical literature, suggests that macroprudential policies can be unpopular with the general public, particularly if they have the result of curbing credit (Horvath and Wagner (2016), Haldane (2017), and Müller (2018)). It is therefore likely that a relatively "strong" regulatory authority at the province level was in a better position to increase down-payment requirements. Consistent with this view, we find that treated province governors and party chairmen are more senior: on average the governors are 2.8 years closer to retirement in comparison to the control cities (56% relative to the 5-year duration of a governor's mandate and about 100% of the average governor tenure we observe in the data), suggesting that they may have greater authority, or that they may be less concerned about potential negative career consequences of their policy.

A second question is what policy implications we can draw from our findings. Since the financial crisis of 2007-2009, evidence has accumulated documenting the potential negative effects of household leverage, and how high levels of debt exacerbate the business cycle (Lamont and Stein (1999), Almeida, Campello, and Liu (2006), Mian, Rao, and Sufi (2013), Mian, Sufi, and Verner (2017), Baker (2018)). Macroprudential tools, including LTV caps, have been the focus of much of the debate on how to design policies to contain household leverage (Allen and Carletti (2011), Aikman et al. (2019)), and there is evidence showing that they can be effective (Almeida, Campello, and Liu (2006), Igan and Kang (2011), Claessens, Gosh, and Mihet (2013)). Our results, however, point to a vulnerability of LTV caps to regulatory arbitrage, fueled by lightly regulated credit channels such as P2P platforms. Understanding the policy implications of this finding revolves around three further questions.

First, is the type of regulatory arbitrage we document confined to P2P credit, or could it be run with alternative credit channels? A salient channel could be credit card debt, which has similar interest rates as P2P credit.[33] Institutional features of the Chinese financial system suggest that is unlikely: Credit card penetration rates in China, as well as the volume of credit card debt, are still relatively low (consistent with per capita GDP being low in comparison to more mature economies).[34] Abstracting from the Chinese context, in the U.S. credit card debt has a worse impact on the borrower's FICO score than P2P loans, and also in the rest of the world it is generally more transparent to banks and other mortgage lenders. [35] In sum, it takes P2P credit, or something with similar contractual and regulatory characteristics as P2P credit, to run the kind of regulatory arbitrage we analyze.

[33] Credit card interest rates are on average about 20%; for P2P credit in the U.S., Balyuk (2017) reports interest rates of about 18% and Morse (2015) a range of 13-19%. Our own data indicate interest rates at the lower end of that range (Table 1).
[34] As of 2013, the average Chinese had 0.29 cards, in contrast to the average American who had over 3. Moreover, outstanding credit card debt is small (2% of GDP in 2013, versus 11% in the U.S.), and credit card debt must typically be repaid on a much shorter horizon than P2P credit (1 month versus an average loan duration of 2-3 years in our data). These features suggest that credit cards are unlikely to play as a relevant a role as P2P credit in the Chinese context.
[35] Raising the limit on one's credit card triggers a "hard" inquiry, which remains on the borrower's credit report for two years (affecting her FICO score), regardless of whether or not the limit increase is granted; in contrast, applying for a P2P loan only results in a "soft" inquiry, which is not reported on the credit report and does not affect the FICO score. In addition, credit

Second, given our evidence, should we consider curbing P2P credit via regulation, and if so, to what extent? There are theoretical and empirical arguments suggesting that P2P credit in its current form can be welfare-increasing. One is that precisely its light regulation allows it to serve a pool of potentially profitable borrowers who would otherwise remain unbanked. Another reason is that the entry of the P2P lending technology, and its lower loan origination costs, creates competition for bank lenders (Buchak et al. (2018)), Morse (2015), de Roure, Pellizzon, and Thakor (2018)). Moreover, P2P credit is disintermediated and lenders can directly match their investment horizon to the loan maturities available on the platform. This allows the lenders to extend loans without the rollover risk associated with maturity transformation. These benefits must be weighed against the possibility of abuse and regulatory arbitrage of the sort we document, and assessing their relative importance seems far from trivial.

Third, assuming that we would like to limit P2P credit, how does one determine and enforce that limit? An ongoing discussion among Chinese regulators has focused on the introduction of caps to the amount of lending and borrowing that a given individual can do on P2P platforms. The proposed caps, however, would typically not be binding against the regulatory arbitrage that we analyze: a proposal from August 2016 indicated a target cap of RMB 200,000 for household borrowing on a given platform, i.e. over five times larger than the about RMB 36,000 increase in P2P borrowing at the treated cities following November 2013 (Huang (2018)).

An alternative approach is to broaden the scope of mortgage credit regulation to ratios other than LTV, such as debt-to-income (DTI), which take into account the entire debt position of the prospective borrower; and indeed the literature on macroprudential regulation discusses DTI as a relevant additional tool (Crowe et al. (2012)). That, however, requires setting up a credit registry; and monitoring P2P loans implies collecting information to a level of detail which, to the best of our knowledge, is unprecedented

card debt is classified as "revolving", whereas P2P loans are classified as "instalment" debt; revolving debt has a worse impact on the FICO score.

in most developed economies. This problem is coupled with two additional issues. First, DTI and LTV caps serve different policy goals and they are complementary rather than alternative policy instruments.[36] As a result, tighter DTI caps cannot fully compensate for the circumvention of LTV caps via P2P credit. Second, tighter DTI caps can be procyclical, in that they can prevent (efficient) borrowing to smooth consumption over the business cycle. That seems in contrast with the aims of macroprudential regulation, which involve precisely preventing the financial system from amplifying business cycle fluctuations.

VIII. Conclusion

We investigate the capacity of P2P credit to undermine loan-to-value (LTV) caps in mortgage markets. We rely on a novel, hand-collected database containing all lending transactions at RenrenDai, a leading Chinese P2P credit platform, and focus on the increase in 2013 of minimum down-payment requirements on second-home mortgages at several major Chinese cities. This tightening of LTV caps should raise the demand for P2P credit by borrowers, who try to circumvent the new down-payment requirement. Consistent with this argument, P2P loans increase at the treated cities relative to the control cities following the new LTV cap. Importantly, the structure of our data allows us to separate credit demand and supply effects, using a lender × date fixed effects strategy – we are thus able to isolate the capacity of the P2P channel to fuel household debt. We validate this analysis with evidence from a reverse change in LTV caps in 2015, when city governments lowered 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 credit that have been observed by part of the literature may be limited. Our results indicate that P2P credit can act as a channel to circumvent LTV caps affecting loans made by traditional credit providers. The rapid growth of P2P credit in recent years and its largely unregulated and informal nature

[36] DTI caps assure that borrowers take on affordable mortgages, whereas LTV caps prevent speculation in the housing market by forcing the borrower to have "skin in the game".

suggest that a policy solution may not be trivial. More broadly, our findings add to the growing body of results suggesting that, at least in part, FinTech development is driven by regulatory arbitrage; complementing those earlier results, they suggest that regulatory arbitrage on the side of credit demand, not only supply, may also be economically important.

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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 May 2012-May 2015 ($\pm$ 18 months around the November 2013 tightening of mortgage down-payment requirement) 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
Proportion of months delinquent (%)	1.96	11.35	0	0	100	107,502
Default (0/1)	0.02	0.14	0	0	1	78,289
B. Borrower characteristics						
Income (monthly RMB)	11,334	13,254	0	5,000	50,000	107,494
Age	37.74	8.41	23	36	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
Married (0/1)	0.71	0.45	0	1	1	107,502
Home owner (0/1)	0.50	0.50	0	1	1	107,502
Number of applications since registration	1.35	3.54	1	1	148	107,502
Total amount borrowed since registration (RMB)	66,079	99,927	3,000	53,600	9,000,000	107,502
Number of lenders per loan	44.87	55.06	1	30	1,841	107,457
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	1,975	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
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 mortgage down-payment requirements. All variables are defined in detail in the appendix. 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	11,873	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
Married (0/1)	0.71	0.73	-0.02	-0.988
Home owner (0/1)	0.18	0.27	-0.09	-2.040**
Number of applications since registration	1.51	2.06	-0.56	-0.974
Total amount borrowed since registration (RMB)	69,501	65,005	4,494	0.536
Number of lenders per loan	33.37	33.81	-0.44	-0.272
B. Lender characteristics				
Portfolio size (RMB)	464,976	488,243	-23,266	-0.826
Portfolio size (nr. loans)	262.7	269.9	-7.173	-0.573
Uplan lending (% of RMB)	68.88	71.57	-2.698	-0.637
Uplan lending (% of loans made)	72.72	75.51	-2.790	-0.652
Experience (months since first loan)	5.505	5.410	0.094	-0.433
C. Macroeconomic characteristics				
Province GDP per capita (RMB)	60,301	46,991	13,310	1.060
Province population (× 10,000)	5,251	6,249	-998	-0.649
Province annual GDP per capita growth (%)	8.16	11.20	-0.03	-1.336
Province annual population growth (%)	1.04	0.76	0.28	0.690
House price index	0.20	0.15	0.05	0.874
% change in house prices (past 6 months)	17.67	17.62	0.05	0.104
Household net debt-to-income	-0.745	-0.422	-0.323	-1.299
Real wage index	1.425	1.613	-0.188	-0.826
Annual real wage growth (%)	0.4	0.7	-0.3	-0.912
Unemployment rate (%)	13.4	14.5	1.5	0.544
RenrenDai penetration (applications per 10,000 inhabitants)	1.725	1.411	0.314	0.773

Table 3 P2P lending around the 2013 increase in mortgage down-payment requirements: City level
In columns (1)-(4), 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 month t. The dependent variable is the log-loan amount associated with the aggregate loan applications or RMB 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 following the change in mortgage down-payment requirements; in all specification the sample period covers a window of ± 18 months around the down-payment requirement increase. Specifications (1) and (2) focus on loan applications and specifications (3) and (4) on loans that are actually granted. To control for serial correlation in the standard errors, we time-average and collapse the data (Bertrand, Duflo, and Mullainathan (2004)), and estimate:

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

where ΔL_c denotes the change in log-loan amount from before to after the change in down-payment requirements. In columns (5) and (6), a similar regression specification is estimated, where the dependent variable is the monthly growth rate in house prices. In all specifications, the vector of control variables x includes province GDP and population level and past growth rates, and yearly real wages and wage growth, city unemployment rate, city house affordability index and city-level net household debt over income. Specifications (1)-(4) also include city level house price % growth over the past 6 months. 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.

	Credit volumes					
	Applications		**Loans**		**House prices growth**	
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated$	0.086***	0.062***	0.027*	0.031**	0.001	0.003
	(0.016)	(0.016)	(0.016)	(0.015)	(0.003)	(0.003)
Controls	N	Y	N	Y	N	Y
R^2	0.40	0.60	0.29	0.56	0.10	0.29
N	52	52	52	52	51	51

Table 4 P2P lending around the 2013 increase in mortgage down-payment requirements: Lender-borrower level
The table reports the estimates of:

$$\Delta L_{lb} = \alpha + \delta Treated_{bc} + \mu' \Delta x_{bc} + \varepsilon_{lb}$$

Each observation corresponds to a given pair borrower b-lender l. The dependent variable is the change in the natural logarithm of loans made by lender l to borrower b (average after the 2013 increase in down-payment requirements minus average before that). $Treated$ is an indicator variable equal to 1 if borrower b is located in a city c that belongs to the treatment group (Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenyang, Shenzhen, and Wuhan). Following Bertrand, Duflo, and Mullainathan (2004), the equation is estimated on changes around the down-payment requirement increase, after collapsing and time-averaging the data around the policy intervention. All specifications except (4) include lender fixed effects, corresponding to controlling for a lender-specific intercept before and after the 2013 increase in down-payment requirements. In Panel A, specifications (1)-(4) focus on loan volumes in the full sample, specification (5) on the sub-sample of borrowers who borrow on RenrenDai both before and after the down-payment increase, and specification (6) on the subset of borrowers who borrow on RenrenDai only after. Panel B reports a number of additional checks: in specifications (1) and (2), the treated cities are separated into "Tier 1" (Beijing, Guangzhou, Shanghai, and Shenzhen) and "Tier 2" cities (all other treated cities). In specifications (3) and (4), the sample is restricted to include only lenders who have been active on RenrenDai prior to November 2013, either because they registered (specification (3)), or because they actually made a loan (specification (4)). Specifications (5) and (6) include additional controls on the city level (log-per capita GDP, log-population, per capita GDP growth rate, and population growth rate, specification (5)), and interact all controls with the $Post$ indicator (specification (6); following the time-average-and-collapse approach of Bertrand, Duflo, and Mullainathan (2004), this is implemented by including in the regression the average pre-2013 level of all control variables). In both panels and all specifications, growth controls include province GDP per capita growth rate over the past 12 months, province population growth rate over the past 12 months, and the % change in the house price index in the previous 18 months. Level controls include province GDP per capita, province population, and house price index levels. Labor market controls include city-level unemployment rate, yearly real wages, and real wage growth. Household finance controls include city-level household net debt over income. 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. Baseline

	Full Sample				**Intensive margin**	**Extensive margin**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated$	0.023*	0.035***	0.034**	0.045**	0.008	0.034**
	(0.013)	(0.012)	(0.013)	(0.022)	(0.014)	(0.013)
Controls:						
Growth	Y	Y	Y	Y	Y	Y
Levels and Labor market	N	Y	Y	Y	Y	Y
Household finance	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	0.050	0.60	0.39
N	4,677,495	4,677,495	4,677,495	4,690,509	86,958	4,573,954

B. Additional Results

	Treated city:		Pre-2013 active lenders:		Additional controls:	
	Tier 1	**Tier 2**	**Registered**	**Lent**	**City Controls**	**Controls Interacted**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated$	0.117*	0.024**	0.061***	0.067***	0.037***	0.034***
	(0.068)	(0.011)	(0.021)	(0.022)	(0.010)	(0.012)
Controls:						
Growth	Y	Y	Y	Y	Y	Y
Levels and Labor market	Y	Y	Y	Y	Y	Y
Household finance	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y
R^2	0.39	0.37	0.267	0.24	0.39	0.39
N	3,772,547	4,049,120	2,673,671	2,457,154	4,677,495	4,677,495

Table 5 Credit volumes, borrower home ownership, and house price growth

The table reports the estimates of regressions with identical specification as in Table 4, estimated over alternative sub-samples. Specifications (1)-(2) focus on borrower home ownership (Y/N); specifications (3)-(4) on the borrower's city house price growth rate (High – above the median/Low – below the median). The standard errors (reported in parentheses) are clustered at the city level. The row labeled F test (p-value) below columns (1)-(2) and (3)-(4) reports the F test statistic (and the associated p-value) for the difference between the estimates of the coefficients on the $Treated$ indicator in the corresponding columns. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

	Borrower home owner		**Borrower city house prices growth forecast**	
	Yes	**No**	**High**	**Low**
	(1)	(2)	(3)	(4)
$Treated$	0.052***	-0.002	0.077***	0.022***
	(0.011)	(0.020)	(0.024)	(0.008)
Controls:				
Province	Y	Y	Y	Y
Labor market	Y	Y	Y	Y
Household finance	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
R^2	0.36	0.40	0.39	0.37
N	3,865,736	3,955,877	3,888,534	3,933,161
F test (p-value)	9.00*** (0.018)		5.25** (0.024)	

Table 6 Credit volumes and lender characteristics

The table reports the estimates of regressions with identical specification as in Table 4, estimated over alternative sub-samples defined by lenders' characteristics. Specifications (1)-(2) focus on whether the lender makes a loan via Uplan or direct peer-to-peer, specifications (3)-(4) on whether the lender's experience is low or high (below/above the median), specifications (5)-(6) on whether the lender's portfolio size is small or big (below/above the median). The row labeled F test (p-value) below columns (1)-(2), (3)-(4) and (5)-(6) reports the F test statistic (and the associated p-value) for the difference between the estimates of the coefficients on the $Treated$ indicator in the corresponding columns. 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.

	Lending channel		**Experience**		**Portfolio Size**	
	Uplan	**Direct**	**Low**	**High**	**Small**	**Big**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated$	0.042***	0.006	0.016**	0.021*	0.022**	0.033***
	(0.012)	(0.012)	(0.007)	(0.010)	(0.090)	(0.012)
Controls:						
Province	Y	Y	Y	Y	Y	Y
Labor market	Y	Y	Y	Y	Y	Y
Household finance	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y	Y	Y
R^2	0.35	0.60	0.72	0.36	0.60	0.33
N	3,672,033	998,775	2,361,956	2,311,742	2,326,763	2,348,874
F test (p-value)	11.90*** (0.001)		0.31 (0.581)		5.71** (0.020)	

Table 7 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 loan, made to a given borrower b on a given calendar date t. The dependent variable y_{bt} is the on-site verification indicator (specification (1)), the borrower's credit score ((2)), the interest rate spread associated with the loan ((3)), and the natural logarithm of the loan's time to maturity ((4)). $Treated$ 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. In all specifications, the vector of control variables x includes city fixed effects, calendar month fixed effects, administrative region × calendar month fixed effects, city-level house price % growth over the past 18 months, borrower age, income, college degree, gender, number of applications the borrower, total amount borrowed since registration, number of lenders per loan, and yearly macroeconomic controls province GDP and population level and past growth rates, city-level unemployment rate, real wage level and wage growth, and city-level household net debt over income (in these specifications, fixed borrower characteristics and yearly macroeconomic controls are dropped). 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.

	On-site Verification	**Credit Score**	**Spread**	**Duration**
	(1)	(2)	(3)	(4)
$Treated \times Post$	-0.047	-0.008	0.000	0.003
	(0.052)	(0.031)	(0.001)	(0.021)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Region × Month FE	Y	Y	Y	Y
R^2	0.58	0.23	0.53	0.53
N	103,181	103,062	103,225	103,225

Table 8 P2P Loan performance following the 2013 increase in down-payment requirements

The table reports the estimates of regression specifications analogous to Table 7, focused on loan performance. In specification (1), the dependent variable is delinquency, defined as the percentage of months during the borrowing period in which the borrower is delinquent; in specification (2), it is a default indicator. Specifications (3)-(4) focus on the loss conditional on default on a given loan; because these tests are restricted to loans that default, the number of observations is reduced. In specification (3), the dependent variable is the natural logarithm of the RMB loan amount; in specification (4), it is the natural logarithm of the outstanding amount of the loan at the time of default (i.e. the amount of the loan that has not yet been repaid when default occurs). In all specifications, the vector of control variables x is the same as in Table 7. 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.

			Loss given default	
	Delinquency	**Default**	**Loan size**	**Outstanding loan amount**
	(1)	(2)	(3)	(4)
$Treated \times Post$	0.011***	0.006*	3.573***	0.291***
	(0.004)	(0.003)	(0.748)	(0.078)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Region × Month FE	Y	Y	Y	Y
R^2	0.22	0.13	0.22	0.16
N	103,225	91,836	1,429	1,429

Table 9 P2P lending around the 2015 decrease in down-payment requirements

Panel A reports the estimates of regressions analogous to Table 4, 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 and panel C report the estimates of regressions analogous to Tables 7 and 8, estimated again around the September 2015 decrease in down-payment requirements. The control variables are the same as in the regressions of Table 7. 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)
$Treated$	-0.060**	-0.029**	-0.010	-0.029**
	(0.025)	(0.013)	(0.009)	(0.013)
Controls	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Lender FE	N	Y	Y	Y
R^2	0.02	0.38	0.45	0.38
N	19,087,041	19,059,813	395,461	18,605,512

B. Loan pricing and screening of the borrowers

	On-site verification	**Credit score**	**Spread**	**Duration**
	(1)	(2)	(3)	(4)
$Treated \times Post$	-0.065	-0.043	-0.001***	-0.056***
	(0.069)	(0.043)	(0.000)	(0.015)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Region × Month FE	Y	Y	Y	Y
R^2	0.62	0.24	0.49	0.48
N	212,276	212,170	197,103	212,291

C. Loan performance

			Loss given default	
	Delinquency	**Default**	**Loan size**	**Outstanding loan amount**
	(1)	(2)	(3)	(4)
$Treated \times Post$	0.000	-0.011*	-0.124	-0.092*
	(0.012)	(0.006)	(0.574)	(0.052)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Region × Month FE	Y	Y	Y	Y
R^2	0.53	0.15	0.17	0.14
N	212,291	108,206	1,868	1,868

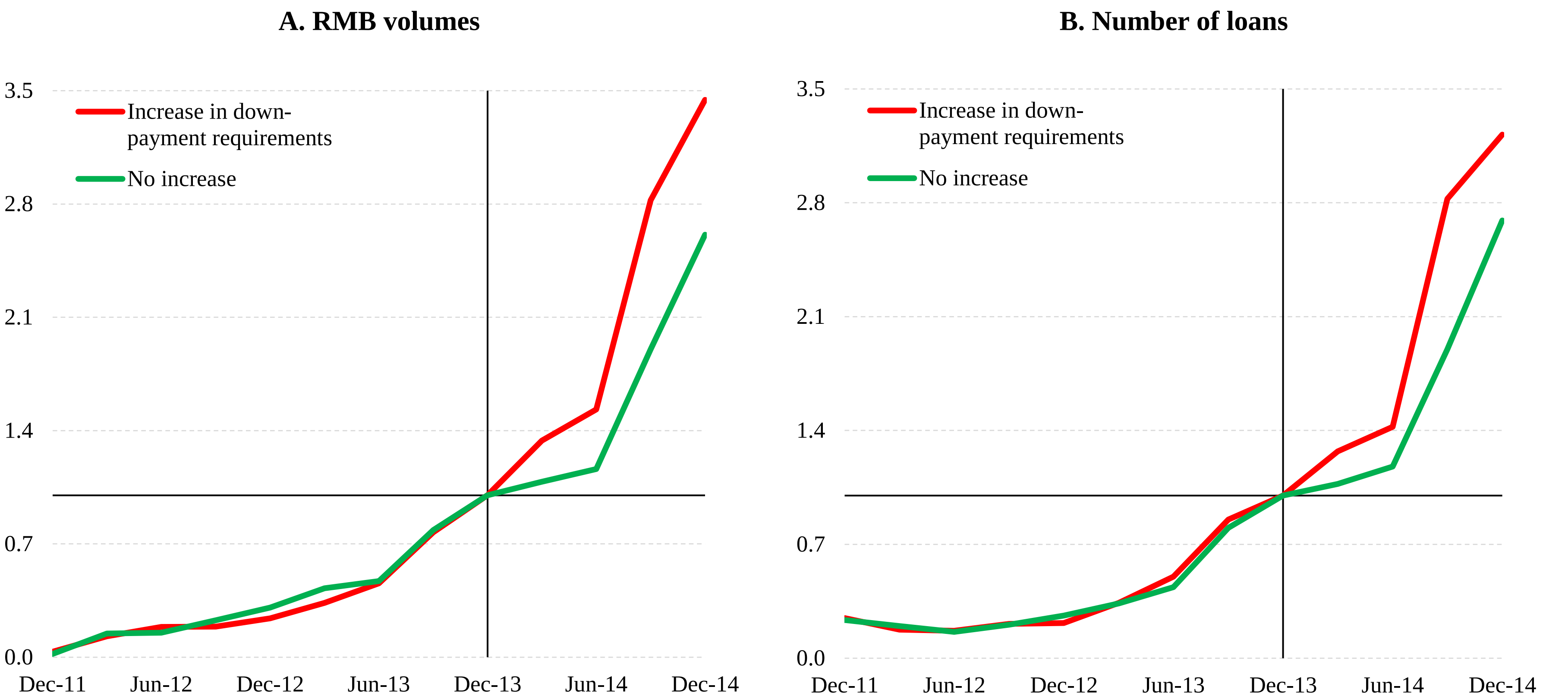

Figure 1 P2P loan applications at RenrenDai around the 2013 increase in down-payment requirements

The graphs plot the P2P loan applications 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 RMB 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 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 down-payment requirements increase, the growth in P2P loan applications in the treated cities is higher than in the control cities.

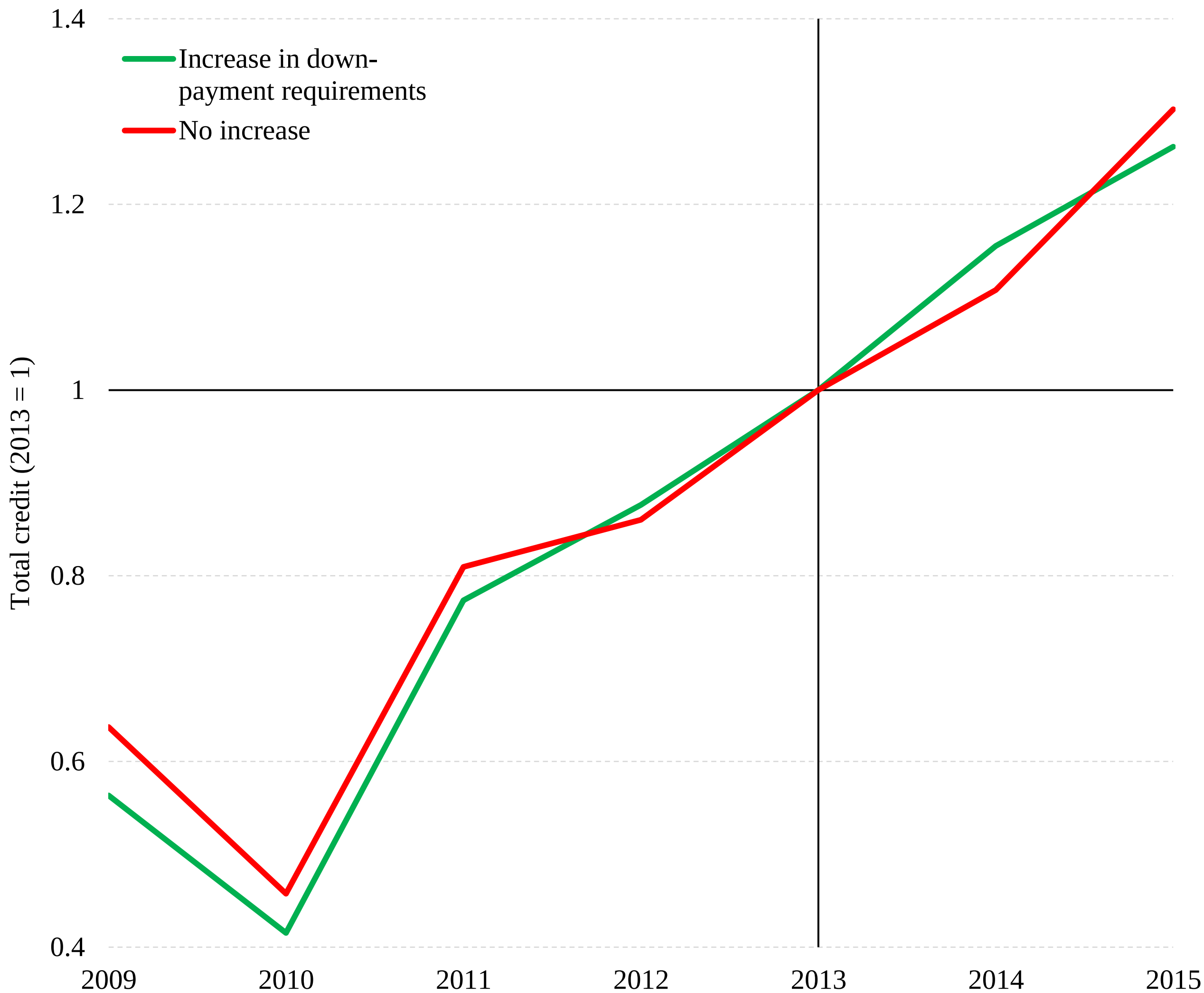

Figure 2 Total credit by Chinese financial institutions around the 2013 increase in down-payment requirements
The graphs plots the total credit extended by Chinese financial institutions, for treated and control cities, around the 2013 increase in mortgage down-payment requirements. The vertical axis reports the city-level RMB total credit, 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 all cases, total credit is rescaled so as to equal 1 in 2013. The graph shows no noticeable difference in the growth of total credit between treated and control cities after the increase of down-payment requirements.

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 one-year Shibor rate.
Duration (months)	Maturity of the loan, expressed in number of months.
On-site verification (Y/N)	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.
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)	Indicator 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: 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 RMB.
Age	Age of the borrower at the origination of the loan.
College degree (0/1)	Indicator variable that takes the value of 1 if the borrower has a college degree or higher education level.
Male (0/1)	Indicator variable that takes the value of 1 if the borrower is a male.
Home Owner (0/1)	Indicator variable that takes the value of 1 if the borrower owns a house and 0 otherwise.
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.
Total Amount Borrowed since registration	Total RMB borrowed by the borrower on Renredai at the time of the loan origination since her registration
C. Lender characteristics	
Portfolio size (RMB)	Size of lenders's portfolio, measured in RMB.
Portfolio size (nr. loans)	Size of lender's portfolio, measured in number of loans.
Uplan lending (% of RMB)	% of the lender's portfolio (measured in RMB) invested via Uplan.
Uplan lending (% of loans made)	% of the lender's portfolio (measured in number of loans) invested via Uplan.

Portfolio concentration (HHI)	Concentration of the lenders' portfolio. Concentration is measured with a Herfindahl-Hirschman index (HHI), based on the relative proportion of each loan with respect to the total size of the lender's portfolio.
Experience (months since first loan)	Experience of the lender, measured as a the number of months between the origination of the loan and the first loan made by the lender on Renrendai.
Number of Lenders per loan	Number of lenders funding a particular loan issue on Renrendai
D. Macroeconomic variables	
Province GDP per capita	GDP per capita of the province where the borrower's city is located, retrieved from the CSMAR database.
Province population	Population of the province where the borrower's city is located, retrieved from the CSMAR database.
Province annual GDP per capita growth	Annual GDP per capita growth of the province where the borrower's city is located, retrieved from the CSMAR database.
Province annual population growth (%)	Annual population growth of the province where the borrower's city is located, retrieved from the CSMAR database.
Monthly % change in house prices (past 18 months)	Average growth of house prices in the city during the past 18 months, retrieved from the China Index Academy databank.
Household net debt to income	Total city household debt minus total city households bank deposits divided by city GDP, retrieved from the CSMAR database.
Real wage index	Average wage per worker in the city divided by the city's CPI (base, Shanghai in November 2013), retrieved from the CSMAR database.
Annual nominal wage growth	Average growth of nominal wages per workers in the city, retrieved from the CSMAR database.
Unemployment rate	Number of unemployed individuals in the city divided by the city labor force, retrieved from the CSMAR database.
RenrenDai penetration	Number of loan applications per city in a given year divided by city population (in thousands) in the same year.
Region	Indicator variable describes the four economic zones defined by the Development Research Center of the State Council in 2005. It takes the value of 1 if the provinces belong to the East zone (Beijing, Tianjin, Hebei, Shandong, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan). It takes the value of 2 if the provinces belong to the Middle zone (Shanxi, Anhui, Henan, Jiangxi, Hubei, and Hunan). It takes the value of 3 if the provinces belong to the West zone (Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang). It takes the value of 4 if the provinces belong to the North East zone (Liaoning, Jilin, and Heilongjiang).