Can Technology Undermine Macroprudential Regulation?

Evidence from Peer-to-Peer Credit in China

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Abstract

We study whether and to what extent peer-to-peer (P2P) credit helps circumvent loan-to-value (LTV) caps, a key macroprudential tool to contain household leverage. We exploit the tightening of mortgage LTV caps in a number of cities in China in 2013 as our testing ground, in a difference-in-differences setting, and we base our tests on a novel, hand-collected database covering all lending transactions at RenrenDai, a leading Chinese P2P credit platform. P2P loans increase at the cities affected by the LTV cap tightening relative to the control cities, consistent with borrowers tapping P2P credit to circumvent the regulation. The granularity of our data allows us to separate credit demand from credit supply effects, with a fixed effects strategy. Our results also indicate that P2P lenders do not adjust their pricing and screening to the influx of new borrowers after 2013, despite the fact that their loans ex post have higher delinquency and default rates. Symmetric effects are associated with a loosening of mortgage LTV caps in 2015. Our test provides empirical evidence on the capacity of P2P credit to undermine LTV caps. More broadly, our analysis informs the debate on the challenges posed by the interaction between FinTech and credit regulation.

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The global crisis of 2007-2009 has alerted economists and regulators about the risks that excessive household leverage poses to the financial system.[1] The debate on how best to contain household debt has focused on macroprudential tools; among them, 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 $90bn (RMB 600bn) as of June 2016, 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. P2P credit can be a channel to elude LTV caps, because it provides borrowers with: (i) a form of anonymity, since P2P platforms typically receive much less regulatory scrutiny than banks, and (ii) access to an unprecedentedly large potential funding pool, in comparison to

[1] There is a vast theoretical and empirical literature on the impact of (household) leverage on the 2007-2009 crisis, too large to sum up here. Part of the theory contributions stress the role of collateralized lending, with arguments based on Kiyotaki and Moore's (1997) seminal work, see e.g. Geanakoplos (2010), Gorton and Ordoñez (2014). Hall (2011) and Guerrieri and Lorenzoni (2017) show that high debt levels can exacerbate the downturn of the economic cycle even in the absence of collateralized lending. 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), Hanson, Kashyap, and Stein (2011), Claessens (2015), Jácome and Mitra (2015).

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

[4] G. Wildau, "Chinese P2P lending regulations target hucksters and risk-takers", *Financial Times*, August 24, 2016.

traditional non-bank credit sources such as family and acquaintances, payday lenders, credit cards, etc. We aim to assess to what extent the availability of P2P credit poses a vulnerability to LTV-based policies and contributes to fueling household debt creation.

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. Since Koopmans (1949), the approach to identify supply is to trace it out with demand shifts. Thus, we require a shock to the demand for P2P lending, which does not separately affect its supply.

Second, in order to trace out credit supply with demand shocks, we must control for potential supply-side drivers, mainly in the form of unobserved heterogeneity among P2P lenders. For instance, lenders may differ in terms of their proximate knowledge, due to their expertise (Morse (2015)) or their ability to harness information from social circles for screening and monitoring (Freedman and Jin (2014), Lin, Prabhala, and Viswanathan (2013)). To the extent that lenders' characteristics such as these can vary with the exposure of their borrowers to a demand shock, the resulting simultaneous changes in 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 takes place in November 2013. The city governments of a number of large Chinese cities impose a 16.7%

increase in the minimum down-payment required to obtain a mortgage for the purchase of a second home, raising it from 60% to 70% of the property's value. The objective is to slow down the growth in real estate prices, following a policy impulse in this direction by the Chinese central government.[5] Anecdotal evidence, however, suggests that real estate investors circumvent the new requirements, borrowing via P2P credit platforms to meet the increased down-payment.[6] In other words, with a relatively small P2P loan, households are able to increase their leverage by the (much larger) full amount of the mortgage. Importantly, the regulatory change creates a positive shock to P2P credit demand, thus addressing our first empirical challenge.[7]

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

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[5] "Shanghai Raises Home Down-Payment Requirement as Prices Jump", *Bloomberg*, November 8, 2013, and "China's Nanjing, Hangzhou Raise 2nd Home Down Payments", *Bloomberg*, November 27, 2013.

[6] D. Weinland, and Y.Yang, "China to Crack Down on P2P Lenders," *Financial Times*, March 14, 2016.

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

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 boom in 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. These findings are in line with our key predictions, and provide a first piece of evidence consistent with P2P credit being instrumental to circumventing the regulatory LTV cap.

Our subsequent tests validate this visual check, and strengthen the case for a causal interpretation. City- and borrower-lender level regressions confirm the evidence from Figure 1. In particular, we leverage the depth of our data with the borrower-lender level regressions, which allow us to trace the 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 10% of the increase in down-payment requirements for large cities like Shanghai or Beijing, and over 35% in smaller 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)), this estimate provides a lower bound on the importance of P2P lending as a channel to circumvent regulatory LTV caps. Consistent with this view, the regulatory intervention itself appears largely 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 (tighter screening would imply increases for both), nor do we observe any significant changes in loan yields or maturities. This is in spite of the fact that default rates increase, driven primarily by "new" borrowers, who come to RenrenDai only after November 2013. These results suggest that lenders have an "inflexible" lending technology, and do not adjust their lending decisions, even though they are making loans that turn out to be riskier.

We validate this analysis studying a symmetric change in LTV caps, which takes place in September 2015. Starting from that month, all the city governments in China, with the exceptions of Beijing, Guangzhou, Sanya, Shanghai, and Shenzhen, impose a 16.7% reduction in minimum down-payment requirements, 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 decreases relative to the controls, reversing the effects observed around the 2013 episode.

Our findings make three contributions. First, to the best of our knowledge, this is the first paper empirically studying the interaction between new financial technologies and credit regulation. One could view FinTech, and in particular P2P lending, as a form of shadow banking. Regulatory arbitrage has long been considered one of the main drivers of the growth of shadow banking. Interestingly, however, a large part of the literature has focused on the elusion of regulatory constraints by financial intermediaries such as banks, i.e. on the side of credit *supply* (Adrian and Ashcroft (2012), Plantin (2014)). Our results are consistent with the view that regulatory arbitrage on the side of credit *demand* (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, Loualiche, Plosser, and Sauvagnat (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, Dell'Arriccia, Igan, and Laeven (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 – 2010-2016 – 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 tool on which much of the debate on macroprudential regulation has focused (Allen and Carletti (2011), Crowe, Dell'Arriccia, Igan, and Rabanal (2011), Claessens (2015), Jácome and Mitra (2015)). A potential solution would be to monitor other indicators than LTV (for example, debt-to-income), 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 successful in the first place.

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

II. Predicted impact of the change in LTV caps

We analyze the impact of the unregulated P2P credit channel on the effects of changes in regulatory LTV caps (mortgage down-payment requirements), using 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, aggregate interest costs, and defaults are not reduced. These results allow us to formulate the key empirical predictions for our proposed test.

First, we consider an economy populated by households (borrowers) and competitive traditional, regulated lenders ("banks"). At a later stage, we introduce 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 will use to pay back their loans. The probability of positive cash flows $\Pr(Y = y) = p$ takes values in $\{p_L, p_H\}$, with $p_H - p_L = \Delta_p > 0$. A borrower needs to exert "effort" to raise the success probability to p_H, and the borrower's utility from not exerting effort is B.

Each would-be borrower has assets-in-place A, 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 $y = d_b + d_l$. If the borrower defaults, the bank recovers a value $R < I$ (e.g. as the result of a foreclosure process).[8] R is exogenously given.[9] 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 $y = d_l + d_b$, and assuming $y \geq B/\Delta_p + d_l$, we have the following condition for the bank to make a loan:

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

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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[8] 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.

[9] 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 (5), and the aggregate interest costs are reduced. Finally, because there are fewer borrowers, there are also fewer aggregate defaults $(1 - p_H)[1 - G(\bar{A} + \delta)]$. In sum: tightening the LTV cap reduces new credit, as well as aggregate interest payments and defaults.

What happens when unregulated P2P lenders are introduced? The P2P lenders are assumed to be competitive, as well as "small," in the sense that they cannot lend more than δ to any borrower. These assumptions mimic the features of the P2P lending market in China (Deer, Mi, and Yuxin (2015)). A simple strategy for a 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.

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

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

where the P2P lender payoff is scaled by p_H because the borrower also receives credit from the bank, which provides the incentive to exert effort.[10]

[10] 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.

For large enough y, this will be true in equilibrium. Because the P2P lenders are competitive, the 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 minimum level of assets-in-place $\bar{A}$ required to obtain credit from the bank is again pinned down by the resource constraint $y = d_l + d_{P2P} + d_b$, and because the $\bar{A} + \delta$ terms in d_l and d_{P2P} cancel out, $\bar{A}$ is again given by expression (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 level of debt in the economy is unchanged. Similarly, the expected number of defaults remains $(1 - p_H)[1 - G(\bar{A})]$. Also similarly, aggregate promised interest payments do not change. The interest rate demanded by the P2P lenders, implied by (6), is: $i_{P2P} = \frac{1}{p_H} - 1$. This is larger than i_l, because of the recovery value R. However, the banks make loans with a lower LTV ratio, and as a result demand lower interest. These two effects balance each other exactly. Aggregate interest costs, in other words, are equal to:

$$\underbrace{i_l \times [1 - G(\bar{A} + \delta)]}_{\text{To the bank}} + \underbrace{i_{P2P} \times [G(\bar{A} + \delta) - G(\bar{A})]}_{\text{To P2P lenders}}. \tag{6}$$

Because $\frac{\partial}{\partial \delta}(d_l + d_{P2P}) = 0$, aggregate interest payments are unchanged. In sum: the objective of the tightened LTV cap is to curb new credit, reducing aggregate interest costs and aggregate defaults. The availability of P2P credit, however, sterilizes the cap, leaving new credit, aggregate defaults, and aggregate promised interest payments 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

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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.

credit in the economy, but simply shift demand into and out of P2P lending. Therefore: Following the 2013 increase in down-payment requirements, we will observe a larger volume of new P2P loans in cities that raise mortgage down-payment requirements (treatment group) than in other cities (control group).[11]

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. 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 over 3 million registered accounts (2016). 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 November 2016. In total, the data contain 909,649 loan applications, made by 703,028 individual borrowers, and involving 277,761 lenders.

Table 1 reports summary statistics for out data, over a window of 37 (–18, +18) months around the 2013 mortgage LTV cap tightening. The average loan has a size of RMB 59,674 ($8,730), with an annualized interest rate of 12.5% and duration 27 months. The average RenrenDai borrower has a pre-tax monthly income of RMB 11,000 ($1,610), or about RMB 130,000 ($19,018) 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

[11] This model provides a simple framework to form expectations on the impact of P2P lending on the effectiveness of the 2013 (and, in a further test described below, 2015) policy intervention in the mortgage markets. A byproduct of its simplicity is that aggregate defaults remain unchanged at $(1-p_H)[1-G(\bar{A})]$, because individual borrower default risk is constant. A more flexible model might generate increasing default rates as borrowers turn to P2P lending (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.

74,000 ($10,240).[12] With an average income tax rate of about 40%,[13] 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" (48%), "Consumption/General" (25.7%), and "Entrepreneurship" (8.8%). In their survey of P2P lending in China, Deer, Mi, and Yuxin (2016) find that 51% of survey participants claim to use P2P lending to "accumulate credit worthiness," consistent with borrowing to meet a down-payment requirement, as in the 2013 episode on which we focus. 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 (2016)), the median RenrenDai borrower is a home owner, and about 69% of borrowers who are home owners have a mortgage. Disclosing more information allows the borrower to obtain a higher credit score on RenrenDai's internal rating system, so that borrowers have an incentive to greater disclosure. In our data, 99.86% of all successful loan applications are associated with borrowers who disclose at least some of these non-

[12] 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).

[13] 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.

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 (2016), 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 ($58,197).[14] Portfolios are generally diversified, with an HHI concentration index of 0.007 on average, and the average lender on a given loan 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 Uplan (U计划), an algorithm that matches lenders to borrowers mostly based on returns and maturity preference parameters set by the lender. Around 70% of all loans are made via Uplan.

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 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

[14] The average lender's portfolio size is about three times the annual income of the average borrower in our data. This suggests that RenrenDai lenders are relatively wealthy, and may have some degree of financial sophistication.

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.[15]

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 classic difference-in-differences regression:

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

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:

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

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 are going to be able to estimate model (7)-(7') on different levels of granularity, allowing to control for alternative potential confounding factors. In the simplest specification, we aggregate equation (7') to the city-date level, 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.

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

In a second specification, we estimate model (7) on the individual loan-lender level, i.e. where each observation corresponds to a given loan, associated with a given lender and borrower. This specification allows us to exploit the full depth of our data, and hold the credit supply curve fixed, saturating the model with lender × date fixed effects as discussed (this is equivalent to including lender fixed effects in equation (7')).

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 9% of the population of urban China in our sample on average.[16] 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.

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 cities do not exhibit significant differences in terms of monthly income (RMB 11,216 and 11,872 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: 1.695), and less likely to be home owners (18%, compared to 27% for the control group; t-stat: -2.04).[17] Panel B compares lenders across the two groups. In terms of portfolio size, concentration, experience, and participation to

[16] 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).
[17] 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.

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, 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

We first run a set of preliminary 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 serially correlated 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 imply that, following the 2013 rise in down-payment requirements, the RMB volume of P2P loans in cities affected by the rise increase by 40% on an annual basis (specification (2)), which appears economically substantial.

Separate tests 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 Table 3.B have specification analogous to Table 3.A, where the dependent variable is the quarterly change in house prices in a given city. The implied effects are near zero, and may be positive or negative depending on the specification. In specification (3) we actually 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 1.6 percentage points per quarter. In sum, it appears that the rise in down-payment requirements was largely ineffective in slowing down house price growth at the treated cities.

The evidence from these preliminary tests 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 × date fixed effects. As discussed above, this allows us to hold credit supply fixed, and isolate the effect of a shock to credit demand.

The estimates are reported in Table 4. Specifications (1)-(3) include lender × date fixed effects; specification (4) reports the corresponding estimates without them. Overall, the estimates are in line with 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: they imply a 2.5% monthly increase in P2P lending at the treated cities, or 30% on an annual basis. Compared to the average loan size of about RMB 60,000 (about $8,700), this corresponds to a RMB 18,000 increase.

The value of a medium-size apartment (70 sq. meters) in 2013 in Shanghai, one of our treatment group cities, is RMB 1.8m (about $260,000), so that the increase we document accounts for 10% (= RMB 18,000 / RMB 180,000) of the 10-percentage point increase in down-payment requirements.[18] In tier-2 cities included in our treatment group, like Changsha, Shenyang, and Wuhan, the economic effect is even larger, corresponding to over 35% of the increase in down-payment requirements. Given that RenrenDai,

[18] 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.

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 (borrowers already active on RenrenDai increase their borrowing) and the extensive margin (new borrowers turn to RenrenDai once down-payment requirements increase). To do so, we estimate two additional regressions, in columns (5) and (6). In column (5) (intensive margin), the sample is restricted to borrowers who are active on RenrenDai (have at least one loan) both before and after November 2013. In column (6) (extensive margin), the sample is restricted to borrowers who are active (have at least one loan) only before or only after 2013. The coefficient estimate on $Treated$ in the intensive margin regression is -0.001, indistinguishable from zero; the corresponding estimate in the extensive margin regression is 0.025 (t-stat: 2.08). The difference between the two coefficients is approximately equal to the estimated coefficients on $Treated$ in specifications (1)-(3), suggesting that the effect is driven by the *extensive* margin: in other words, the influx of new borrowers after the 2013 increase in down-payment requirements explains our baseline effect.

Further analysis based on borrower characteristics, reported in Table 5, provides a richer characterization of these findings. 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 12% of the required additional down-payment in tier-1 cities and over 50% in tier-2 cities. We also find that our baseline effect is driven by cities where house price growth over the 18-

month period prior to November 2013 has been above the median.[19] These findings corroborate the link between the increase in P2P credit at the treated cities and the increase in down-payment requirements in November 2013, given that the new regulation only applies to second-home mortgages, and was aimed at overheating real estate markets.

Finally, in Table 6 we partition the sample based on lender characteristics: lending via Uplan/direct lending, experience, and portfolio size. Table 6.A 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)). 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, however, larger in magnitude for lenders with below-median experience.

Table 6.B distinguishes lenders based on their portfolio size.[20] Across lender portfolio size quartiles, the coefficients on $Treated$ are positive; but they are larger and statistically significant in the third and fourth quartiles, suggesting 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 financially more sophisticated, it appears that greater lender sophistication is no obstacle to the increased P2P lending.[21]

[19] The estimates in Table 5 keep the control group observations fixed between the home-owner/non-home-owner and the above/below median house price growth subsamples. In this way, we consider increments in P2P lending that happen both on the extensive margin (more homeowners borrow from the platform in treated cities) and intensive margin (homeowners demand larger loans in treated cities).

[20] Because RenrenDai opens to the public in 2010, the range of lender experience (which we measure as months since making the first loan on RenrenDai) is limited. For that reason, we split the sample by lender experience at the median. In contrast, lender portfolio size has a much larger range, allowing us to split the sample by quartiles.

[21] 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 ($79,500), and the largest portfolio in our sample has size about RMB 4,100,000 ($615,000), indicating that we are looking at individual lenders (rather than e.g. institutions).

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, accounting for 12%-49% of the implied increase in borrowing as per our back-of-the-envelope calculation. The expansion of credit is driven by borrowers from cities that experience faster house prices growth, as well as by a broad range of lenders.[22]

V. Other loan features; loan performance

A. Screening, pricing, and duration of loans

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

Although the treated cities generate an abnormal amount of P2P borrowing after 2013, we find that P2P lenders do not appear to alter their screening in response. Our first measure of screening is on-site verification. Borrowers on RenrenDai self-declare their characteristics such as income, age, etc. In addition, they may also provide on-site verification, whereby an officer from RenrenDai verifies that the information provided is true, by visiting the borrowers at their stated address. If lenders respond to the influx of new borrowers by stepping up screening and tightening their lending standards, they may more frequently demand on-site verification in order to invest in a given loan. We should therefore expect

[22] 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.

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)). Similarly, tighter screening predicts higher borrower credit scores on the loans. However, we also find little evidence of an increased borrower credit score (specifications (3)-(4)). 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 two measures of loan performance: delinquencies (the proportion of months during which the borrower is delinquent over the loan's life) and loan default rates. The sample size shrinks in this case, because of a truncation problem: for some ongoing loans, default may simply not have been declared yet.

The evidence, reported in Table 8.A, indicates a deteriorating loan performance at the treated cities following 2013. We observe an increase in delinquency rates by 0.90 percentage points (specification (1)) and in default rates, also by 0.90 percentage points (specification (2)). Similar to the estimates reported by Morse (2015) for the U.S., default rates are on average about 2% among RenrenDai loans (Table 1). [23] Our estimates imply, therefore, that defaults increase by 45% in relative terms, which appears economically very relevant. Here too, we find that the effect is entirely driven by the extensive margin, and disappears once we control for borrower fixed effects. The interpretation is that the increased default rates occur primarily among "new" borrowers, who register on RenrenDai or start borrowing after 2013, and are thus more likely driven by the minimum down-payment increase.

We further find, in Table 8.B (specifications (1)-(2)), that the increase in defaults is mainly associated with borrowers who are home owners. This is consistent with our earlier results, as home owners are more likely attempting to circumvent the minimum down-payment increase. We combine this test with a further one, in which we estimate an AR(1) model for house price indexes, obtaining house price growth forecasts for the treated cities. We then compute forecast errors, and run separate tests for cities where the forecast proves to be higher/lower than actual house price growth (specifications (3)-(4)). We find that the increase in defaults is estimated more precisely in cities where house price growth underperforms the forecast, but the point estimates are similar across the two groups.

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.

[23] 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. In particular, the 2015 default wave does not appear to have affected the treated cities in our test differently from the control cities.

VI. Evidence on the 2015 episode

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

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

Bearing these caveats in mind, we run tests similar to the ones presented in Sections IV and V. First, we examine changes in lending volumes following September 2015, comparing "treated" and "control" cities, where the treatment group includes all Chinese cities with the exception of Beijing, Guangzhou, Sanya, Shanghai, and Shenzhen, which form the control group. The results are illustrated in Table 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 abandon the P2P channel altogether. In economic terms, the effects are similar to the ones presented in Section IV, but with the reverse sign.

Second, we look at lending outcomes, in Table 9.B. Once again, we do not observe large changes in screening: the coefficient estimate in specification (4) on on-site verification, although statistically significant, is economically small at 2.4 percentage points; furthermore, we do not find any significant changes in credit scores, and the magnitude of the coefficient estimate in specification (3) is economically negligible. Given that, following the lowering of down-payment requirement, the P2P lenders should expect *fewer* bad borrowers, there is no reason they should tighten their screening.

We do observe statistically significant changes in the loan terms (pricing and duration), but again they appear economically small. Yield spreads are reduced by about 10 bps, compared to the sample average of nearly 8%; loan duration drops by about 6%, or 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. This is perhaps consistent with the lower sophistication anecdotally associated with P2P lenders, although as we documented RenrenDai lenders have relatively large loan portfolios, suggesting some degree of financial sophistication. On the other hand, this evidence indicates that the benefits of P2P in terms of informal contracting and "proximate knowledge" found by the earlier literature may be limited in this context.

Finally, we do not observe any material changes in delinquencies. Default rates decline by 3.8 percentage points in the treated cities, but the coefficient estimate is at best marginally statistically significant (t-stat: 1.52).

VII. Discussion and policy implications

Since the financial crisis of 2007-2009, evidence has accumulated documenting the negative effects of household leverage, and how high levels of debt exacerbate the business cycle (Lamont and Stein (1999), Mian, Rao, and Sufi (2013), Mian, Sufi, and Verner (2017)). Macroprudential tools have been the focus of much of the debate on how to design policies to contain household leverage (Allen and Carletti (2011), Hanson, Kashyap, and Stein (2011)), and there is evidence showing that they can be effective (Igan and Kang (2011)).

Our findings, on the other hand, point to a vulnerability of LTV caps affecting loans made by traditional credit providers such as banks. Long considered one of the main tools of macroprudential regulation, we provide evidence suggesting that they can be eluded via the P2P credit channel. By themselves, P2P loans are not a threat to financial stability; however, because of the nature of LTV caps, even a relatively small amount of P2P credit can lead to a large mortgage debt.

A policy solution may not be trivial. One possible 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, Dell'Arriccia, Igan, and Rabanal (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 in most developed economies. DTI caps, moreover, may limit households' ability to (efficiently) borrow against future income to smooth consumption over their life cycle. Finally, subjecting P2P platforms to more stringent documentation and transparency requirements risks eroding the very flexibility that makes them a viable business in the first place.

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 loan transactions at RenrenDai, a leading Chinese P2P credit platform, and focus on the increase in 2013 of down-payment requirements on second-home mortgages at several major Chinese cities. This tightening of LTV caps raises 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 experiment in 2015, when city governments lower minimum down-payment requirements, resulting in a drop in P2P credit demand. In either episode, we find little evidence that P2P lenders adjust their policies in response to the expected characteristics of their borrowers, suggesting that the information benefits of P2P 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 (and potentially other macroprudential tools). The rapid growth of P2P credit in recent years and its largely unregulated and informal nature suggest that a policy solution may not be trivial.

References

Adrian, T., and A. B. Ashcraft. 2012. Shadow Banking: A Review of the Literature. Federal Reserve Bank of New York Staff Report 580.

Adelino, M., A. Schoar, and F. Severino. 2012. Credit Supply and House Prices: Evidence from Mortgage Market Segmentation. NBER Working paper 17832.

Adelino, M., A. Schoar, and F. Severino. 2016. Loan Origination and Defaults in the Mortgage Crisis: The Role of the Middle Class. *Review of Financial Studies*, forthcoming.

Agarwal, S., C. Badarinza, and W. Qian. 2017. The Effectiveness of Housing Collateral Tightening Policy. Working paper, National University of Singapore.

Aggarwal, R., and P. Stein. 2016. The Complex Regulatory Landscape for FinTech: An Uncertain Future for Small and Medium-Sized Enterprise Lending, World Economic Forum White Paper 170816.

Albanesi, S., G. De Giorgi, and J. Nosal. 2017. Credit Growth and the Financial Crisis: A New Narrative. NBER Working Paper 23740.

Allen, F., and E. Carletti. 2011. What Should Central Banks Do About Real Estate Prices? Working paper, University of Pennsylvania and European University Institute.

Balyuk, T. 2017. Financial Innovation and Borrowers: Evidence from Peer-to-Peer Lending. Working paper, University of Toronto.

Barrot, J.-N., E. Loualiche, M. C. Plosser, and J. Sauvagnat. 2017. Import Competition and Household Debt. Working paper, MIT Sloan School of Management.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. How Much Should We Trust Difference-in-Differences Estimates? *Quarterly Journal of Economics* 119, 249-275.

Bordo, M. D. 2008. An Historical Perspective on the Crisis of 2007-2008. NBER Working Paper 14569.

Claessens, S. 2015. An Overview of Macroprudential Policy Tools. *Annual Review of Financial Economics* 7, 397-422.

Claessens, S., G. Dell'Arriccia, D. Igan, and L. Laeven. 2010. Cross-Country Experiences and Policy Implications from the Global Financial Crisis. *Economic Policy* 25, 267-293.

Claessens, S., M. A. Kose, and M. E. Terrones. 2012. How do Business and Financial Cycles Interact? *Journal of International Economics* 87, 178-190.

Crowe, C., G. Dell'Arriccia, D. Igan, and P. Rabanal. 2011. Policies for Macroprudential Stability: Managing Real Estate Booms and Busts. IMF Staff Discussion Note 11/02

Crowe, C., and R. Ramcharan. 2013. The Impact of House Prices on Consumer Credit: Evidence from an Internet Bank. *Journal of Money, Credit and Banking* 45, 1085-1115.

Deer, L., J. Mi, and Y. Yuxin. 2015. *The Rise of Peer-to-Peer Lending in China: An Overview and Survey Case Study*. Association of Chartered Certified Accountants.

DiMaggio, M., and A. Kermani. 2017. Credit-Induced Boom and Bust. *Review of Financial Studies*, forthcoming.

DiMaggio, M., A. Kermani, B. Keys, T. Piskorski, R. Ramcharan, A. Seru, and V. Yao. 2017. Monetary Policy Pass-Through: Mortgage Rates, Household Consumption and Voluntary Deleveraging. *American Economic Review*, forthcoming.

Duarte, J., S. Siegel, and L. Young. 2012. Trust and Credit: The Role of Appearance in Peer-to-Peer Lending. *Review of Financial Studies* 25, 2455-2484.

Fang, H., Q. Gu, W. Xiong, and L.-A. Zhou. 2016. Demystifying the Chinese Housing Boom. *NBER Macroeconomics Annual* 30, 105-166.

Foote, C. L., K. S. Gerardi, and P. S. Willen. 2012. Why Did So Many People Make So Many Ex Post Bad Decisions? The Causes of the Foreclosures Crisis. NBER Working Paper 18082.

Foote, C. L., L. Loewenstein, and P. S. Willen. 2016. Cross-Sectional Patterns of Mortgage Debt During the Housing Boom: Stocks and Flows. Working paper, Federal Reserve Bank of Boston.

Freedman, S., and G. Z. Jin. 2014. The Information Value of Online Social Networks: Lessons from Peer-to-Peer Lending. NBER Working Paper 19820.

Geanakoplos, J. 2010. The Leverage Cycle, *NBER Macroeconomics Annual* 24, 1-66.

Gorton, G., and G. Ordoñez. 2014. Collateral Crises. *American Economic Review* 104, 343-378.

Hanson, S. G., A. K. Kashyap, and J. C. Stein. 2011. A Macroprudential Approach to Financial Regulation. *Journal of Economic Perspectives* 25, 3-28.

Holmstrom, B., and J. Tirole. 1997. Financial Intermediation, Loanable Funds, and the Real Sector. *Quarterly Journal of Economics* 112, 663-691.

Igan, D., and H. Kang. 2011. Do Loan-to-Value and Debt-to-Income Limits Work? Evidence from Korea. IMF Working paper 11/97.

Jácome, L. I., and S. Mitra. 2015. LTV and DTI Limits – Going Granular. IMF Working Paper 15/154.

Khwaja, A. I., and A. Mian. 2008. Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market. *American Economic Review* 98, 1413-1442.

Kiyotaki, N., and J. Moore. 1997. Credit Cycles. *Journal of Political Economy* 105, 211-248.

Koopmans, T. C. 1949. Identification Problems in Economic Model Construction. *Econometrica* 17, 125-144.

Lin, M., N. R. Prabhala, and S. Viswanathan. 2013. Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending. *Management Science* 59, 17-35.

Lusardi, A., and P. Tufano. 2009. Debt Literacy, Financial Experiences, and Overindebtedness. NBER Working Paper 14808.

Mian, A., K. Rao, and A. Sufi. 2013. Household Balance Sheets, Consumption, and the Economic Slump, *Quarterly Journal of Economics* 128, 1687-1726.

Mian, A., and A. Sufi. 2009. The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis. *Quarterly Journal of Economics* 124, 1449-1496.

Mian, A., and A. Sufi. 2010. Household Leverage and the Recession of 2007-2009. *IMF Economic Review* 58, 74-117.

Mian, A., and A. Sufi. 2011. House Prices, Home Equity-Based Borrowing, and the US Household Leverage Crisis. *American Economic Review* 101, 2132-2156.

Mian, A., A. Sufi, and F. Trebbi. 2015. Foreclosures, House Prices, and the Real Economy. *Journal of Finance* 70, 2587-2634.

Mian, A., A. Sufi, and E. Verner. 2017. Household Debt and Business Cycles Worldwide. *Quarterly Journal of Economics* 132, 1755-1817.

Morse, A. 2015. Peer-to-peer crowdfunding: Information and the Potential for Disruption in Consumer Lending. *Annual Review of Financial Economics* 7, 463-482.

Plantin, G. 2014. Shadow Banking and Capital Regulation. *Review of Financial Studies* 28, 146-175.

Ravina, E. 2012. Love & Loans: The Effect of Beauty and Personal Characteristics in Credit Markets. Working paper, Columbia Business School.

Schnabl, P. 2012. The International Transmission of Bank Liquidity Shocks: Evidence from an Emerging Market. *Journal of Finance* 67, 897-932.

Schularick, M., and A. M. Taylor. 2012. Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review* 102, 1029-1061.

Shleifer, A., and R. W. Vishny. 1992. Liquidation Values and Debt Capacity: A Market Equilibrium Approach. *Journal of Finance* 47, 1343-1366.

Wei, Z., and M. Lin. 2013. Auction vs. Posted-Price: Market Mechanism, Lender Behaviors, and Transaction Outcomes in Online Crowdfunding. Working Paper, University of Arizona.

Table 1 Summary statistics

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

	Mean	**St. dev.**	**Min**	**Median**	**Max**	**N**
A. Loan characteristics						
Loan amount (RMB)	59,674	53,816	3,000	52,900	3,000,000	107,502
Interest rate (%)	12.49	1.01	7.00	12.60	24.40	107,502
Interest rate spread (%)	7.78	1.07	2.89	7.84	19.81	107,502
Duration (months)	27.06	9.78	1	24	36	107,502
On-site verification (Y/N)	0.77	0.42	0	1	1	107,457
Borrower credit score	171.82	29.71	0	180	181	107,339
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
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
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
Portfolio concentration (HHI)	0.007	0.019	0	0.001	1	107,502
Experience (months since first loan)	6.86	4.31	0	5.80	37	107,502
Number of lenders per loan	44.87	55.06	1	30	1,841	107,457

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	11,872	-656.27	-0.731
Age	39.18	38.73	0.449	1.175
College degree (0/1)	0.51	0.45	0.06	1.695*
Male (0/1)	0.59	0.57	0.02	0.877
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
B. Lender characteristics				
Portfolio size (RMB)	468,649	492,152	-23,503	0.833
Portfolio size (nr. loans)	268.2	275.6	-7.385	0.579
Uplan lending (% of RMB)	68.93	71.64	-2.712	0.640
Uplan lending (% of loans made)	72.76	75.57	-2.805	0.655
Portfolio concentration (HHI)	0.006	0.005	0.001	-0.530
Experience (months since first loan)	4.492	4.396	0.095	-0.745
Number of lenders per loan	33.37	33.81	-0.44	-0.272
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
Monthly % change in house prices (past 18 months)	44.3	60.1	-15.8	0.543
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 wage growth (%)	10.7	11.0	0.3	0.261
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
The table reports the estimates of:

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

Each observation corresponds to a given city c on a given calendar quarter t. The dependent variable is the log-loan amount associated with the aggregate loan applications or actual loan volume in the city. $Treated$ is an indicator variable equal to 1 if the city belongs to the treatment group (Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenyang, Shenzhen, and Wuhan). $Post$ is an indicator variable equal to 1 over the period followinga change in mortgage down-payment requirements. In specifications (1)-(2), the sample period covers a window of ± 1 year around the down-payment increase; in specifications (3)-(4), ± 2 years. Specifications (1) and (3) focus on loan applications, and specifications (2) and (4) restrict the focus to 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 all specifications, the vector of control variables x includes province GDP and population level and past growth rates, city-level house price % growth over the past 18 months, and yearly real wages and wage growth, and city-level net household debt over income. The standard errors (reported in parentheses) are clustered at the city level. Panel B estimates analogous specifications, where the dependent variable is the (change in) house price growth rate in city c, before and after the down-payment requirement increase. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

A. Credit volumes

	$\pm$ 1 year around down-payment requirement increase		*$\pm$ 2 years around down-payment requirement increase*	
	Applications	**Loans**	**Applications**	**Loans**
	(1)	(2)	(3)	(4)
$Treated$	0.105***	0.066*	0.131***	0.074*
	(0.035)	(0.037)	(0.040)	(0.039)
Controls	Y	Y	Y	Y
R^2	0.54	0.49	0.60	0.54
N	51	51	51	51

B. House price growth

	$\pm$ 1 year around down-payment requirement increase		*$\pm$ 2 years around down-payment requirement increase*	
	(1)	(2)	(3)	(4)
$Treated$	0.009	-0.004	0.014**	-0.004
	(0.008)	(0.011)	(0.006)	(0.005)
Controls	N	Y	N	Y
R^2	0.10	0.47	0.14	0.75
N	51	51	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. 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 before or only after. Province controls include province GDP per capita level and GDP growth over the past 12 months, province population level and population growth over the past 12 months, and the % change of the city house prices in the previous 18 months. Labor market controls include city-level unemployment rate, yearly real wages and 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.

	Full Sample				**Intensive margin**	**Extensive margin**
	(1)	(2)	(3)	(4)	(5)	(6)
$Treated$	0.020*	0.025**	0.025**	0.034*	-0.001	0.025**
	(0.012)	(0.012)	(0.012)	(0.019)	(0.013)	(0.012)
Province controls	Y	Y	Y	Y	Y	Y
Labor market controls	N	Y	Y	Y	Y	Y
Household finance controls	N	N	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y
Lender FE	Y	Y	Y	N	Y	Y
R^2	0.39	0.39	0.39	0.03	0.58	0.38
N	5,051,602	5,051,602	5,051,602	5,065,546	94,542	4,938,974

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 symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

	Borrower home owner		**Borrower city house price growth**	
	Yes	**No**	**High**	**Low**
	(1)	(2)	(3)	(4)
$Treated$	0.038***	-0.006	0.014*	0.010
	(0.013)	(0.018)	(0.008)	(0.024)
Province controls	Y	Y	Y	Y
Labor market controls	Y	Y	Y	Y
Household finance controls	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
R^2	0.37	0.40	0.38	0.40
N	4,162,218	4,255,312	4,352,859	4,065,767

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. Panel A focuses on whether a loan is made via Uplan or direct peer-to-peer and whether the lender's experience is low or high (below/above the median). Panel B focuses on the size of the lender's portfolio, which we divide into quartiles. 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. Lending channel and experience

	Lending channel		**Experience**	
	Uplan	**Direct**	**Low**	**High**
	(1)	(2)	(3)	(4)
$Treated$	0.029**	0.008	0.018*	0.012**
	(0.013)	(0.010)	(0.010)	(0.006)
Province controls	Y	Y	Y	Y
Labor market controls	Y	Y	Y	Y
Household finance controls	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
R^2	0.35	0.60	0.65	0.26
N	3,990,351	1,053,846	2,480,133	2,445,586

B. Portfolio size

	Quartile			
	Bottom	**2**	**3**	**Top**
	(1)	(2)	(3)	(4)
$Treated$	0.004	0.017	0.034**	0.032**
	(0.006)	(0.011)	(0.013)	(0.013)
Province controls	Y	Y	Y	Y
Labor market controls	Y	Y	Y	Y
Household finance controls	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
R^2	0.69	0.55	0.42	0.26
N	1,172,187	1,178,507	1,109,200	1,549,134

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 borrower b on a given calendar date t. The dependent variable Y_{bt} is the on-site verification indicator ((1)-(2)), the borrower's credit score ((3)-(4)), the interest rate spread associated with the loan (spec. (5)-(6)), and the natural logarithm of the duration of the loan ((7)-(8)). $Treated$ is an indicator variable equal to 1 if the city belongs to the treatment group (Beijing, Changsha, Guangzhou, Hangzhou, Nanjing, Nanchang, Shanghai, Shenyang, Shenzhen, and Wuhan). $Post$ is an indicator variable equal to 1 over the period following a change in mortgage down-payment requirements (after November 2013 for all treated cities, with the exception of Beijing, where it is equal to 1 following May 2013). In all specifications, the vector of control variables x includes city fixed effects, calendar month fixed effects, administrative region × calendar month fixed effects, 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). Specifications (2), (4), (6), and (8) also control also for borrower fixed effects. The standard errors (reported in parentheses) are clustered at the city level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

	On-site verification		**Credit score**		**Spread**		**Duration**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treated \times Post$	-0.060	0.006	-0.031	0.002	-0.000	-0.002	-0.020	-0.073
	(0.054)	(0.039)	(0.031)	(0.010)	(0.001)	(0.002)	(0.025)	(0.066)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Region × Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FE	N	Y	N	Y	N	Y	N	Y
R^2	0.50	0.98	0.20	0.99	0.45	0.77	0.44	0.90
N	98,601	4,111	98,601	4,111	98,601	4,111	98,601	4,111

Table 8 P2P Loan performance following the 2013 increase in down-payment requirements
The table reports the estimates regressions analogous to Table 7. In panel A, the dependent variable is delinquency, the proportion of months during the borrowing period in which the borrower is delinquent (spec. (1)-(2)), or a default indicator (spec. (3)-(4)). In panel B, the dependent variable is delinquency, and the sample is split between loans to borrowers who own a home or not (spec. (1)-(2)), as well as between loans to borrowers located in cities with high/low (above/below the median) ex post house price forecast error (spec. (3)-(4)). The vector of control variables x is the same as in the regressions of Table 7. Specifications (2) and (4) in Panel A also control also for borrower fixed effects. In both panels and all specifications, the standard errors (reported in parentheses) are clustered at the city level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

A. Full sample

	Delinquency		**Default**	
	(1)	(2)	(3)	(4)
$Treated \times Post$	0.009*	-0.027	0.009*	-0.056
	(0.004)	(0.040)	(0.004)	(0.042)
Controls	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Region × Month FE	Y	Y	Y	Y
Borrower FE	N	Y	N	Y
R^2	0.20	0.65	0.12	0.52
N	98,601	4,111	70,469	3,547

B. Borrower home ownership and house price forecast error

	Borrower home owner		**Borrower city house price forecast error**	
	Yes	**No**	**High**	**Low**
	(1)	(2)	(3)	(4)
$Treated \times Post$	0.010*	0.006	0.008*	0.008
	(0.005)	(0.005)	(0.004)	(0.090)
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	0.21	0.21	0.21	0.21
N	78,304	85,553	83,920	79,937

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 reports 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. Specifications (2) and (4) in Panel A also control also for borrower fixed effects. In all panels and specifications, the standard errors (reported in parentheses) are clustered at the city level. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

A. Credit volumes

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

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

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

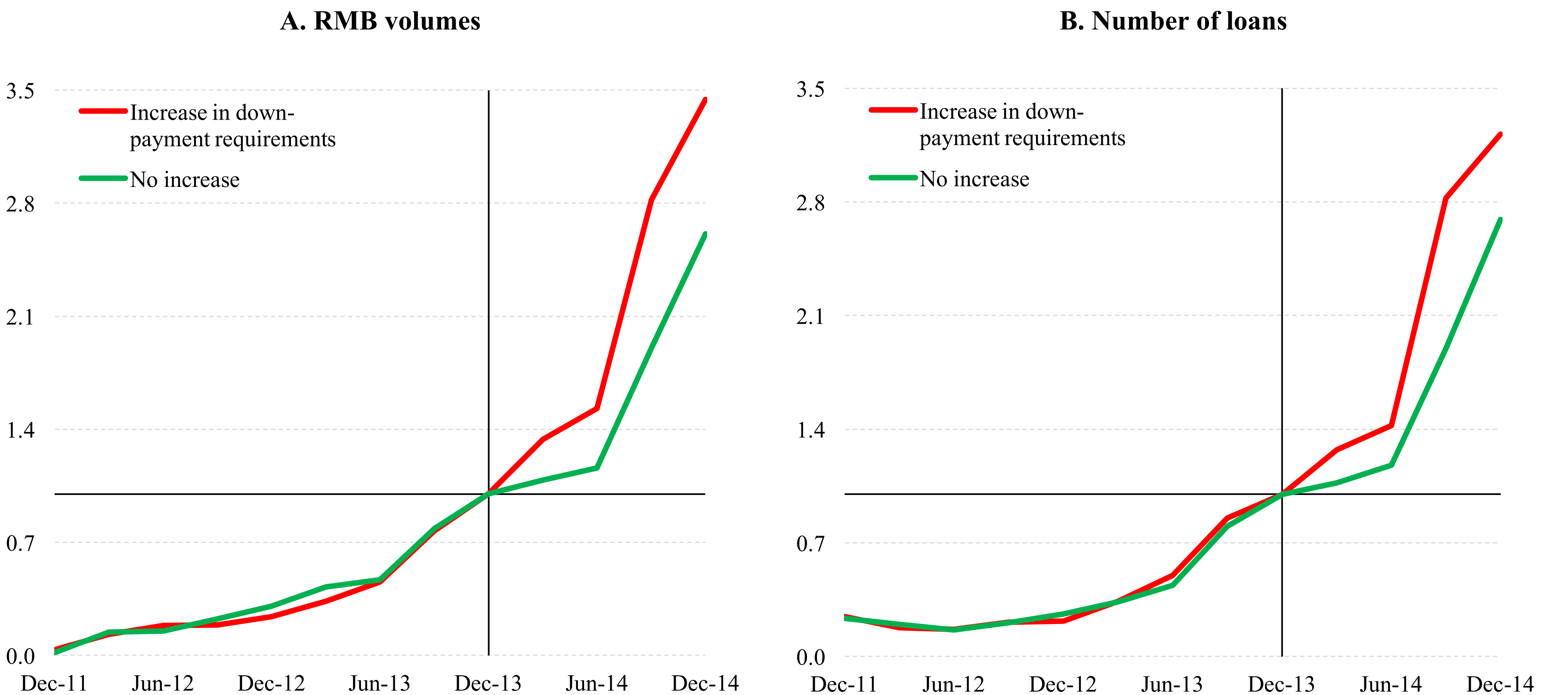

Figure 1 P2P loan applications at RenrenDai around the 2013 increase in down-payment requirements
The graphs plot the P2P loan applications on the RenrenDai platform, for treated and control cities, around the 2013 increase in mortgage down-payment requirements. In panel A, the vertical axis reports 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 increase in down-payment requirements, the growth in P2P loan applications in the treated cities is higher than in the control cities.

Appendix: Variable definitions

Variable	Definition
A. Loan characteristics	
Loan amount (RMB)	Amount of the loan in RMB.
Interest rate (%)	Annual interest rate applied to the loan.
Interest rate spread (%)	Annual interest rate minus the corresponding 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.