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Shadow Bank, Risk-Taking, and Real Estate Financing: Evidence from the Online Loan Market

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Abstract
This paper examines whether and how individual risk-taking behavior affects real estate financing through shadow banks. Using the loan data from an online platform in China, we show that riskier households tend to employ online loans to meet the increasing down-payment in their home purchase. Individual investors are likely to fund riskier real estate loans with higher expected returns. Real estate loans experi- ence higher ex-post default rates than other types of loans. The effect is more pro- nounced during the period of credit constraints.

Keywords Online Lending · Risk Taking · Real Estate Loans · House Purchase Restrictions

JEL Classification G21 · G28 · R21 · R30

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Introduction

The subprime crisis has renewed debate about the necessity of managing the excessive household leverage (Gorton & Ordoñez, 2014; Adelino et al., 2016; Mian & Sufi, 2009, 2011; Mian et al., 2015), which poses excessive risk on the financial system and economic growth (Mian & Sufi, 2009; Di Maggio & Kermani, 2017). Much emphasis has been placed on macroprudential tools targeted at traditional financial intermediaries. But how about if households could circumvent regulated traditional lenders? This study investigates one neglected but lightly regulated lending channel for the household: online lending in shadow banks.

As a dominating category in the shadow banking sector, online lending offers a platform that bridges borrowers and prospective lenders. The shadow banking industry has experienced double-digit growth since the financial crisis due to regulatory arbitrage (Acharya et al., 2016) and the increasing demand for debt roll-over (Chen et al., 2016). Shadow banks provide loan products channeled off the balance sheet to risky and credit-constrained institutions, including small-medium enterprises (SMEs) and real estate developers. Meanwhile, as the low-interest rates environment drives the booming of the real estate market, households resort to alternative ways to meet the increasing down payment in mortgage lending, which makes informal financing a favored option. Employing relatively small loans combined from informal financing, households are viable to get the mortgage from commercial banks. However, it remains unclear whether and how it affects individual investors' risk-taking behavior in shadow banks. Our paper fills the gap.

This paper uses the loan data from an online platform in China. By accessing both the loan and listing data, we can analyze the effect conditional on loan demand to further mitigate the concern of potential endogeneity. Our findings show that, similarly with other shadow banking products designed for corporate, online lending mainly targets risky projects at the individual level. Risky borrowers tend to employ online loans to meet their mortgage requirements in home purchases. The regional evidence further indicates that the real estate loan requests and approval rates tend to be higher in areas with higher home prices and stricter down-payment requirements. Besides analyzing the effect of borrowers' credit risk on the loan origination for home purchase, we examine the loan performance. Particularly, we evidence that when credit is constrained, the issued loans are more likely to default, although the housing restriction policy partially deters the speculation in the real estate market.

We employ China's market as the laboratory. The online loan credit market in China is growing fast, estimated the largest worldwide. In Fig. 1, we plot the consumer loan issuance in China from 2009 to 2017. By June 2016, the online lending volumes totaled over 600 billion RMB ($90 billion), equivalent to 20% of household consumption loans issued by commercial banks.[1] Moreover, to curb the upsurging real estate prices in China's megacities, policymakers frequently intervene in the market via a series of monetary and housing policies. Anecdotal evidence, however,

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

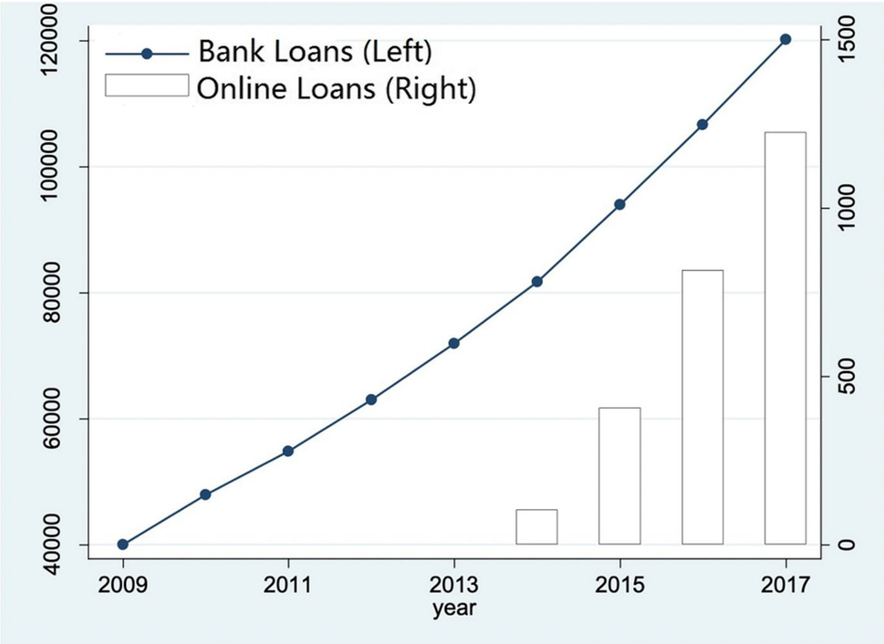

Fig. 1 The consumer loan issuance in China: 2009–2017

suggests that households might circumvent the regulated lenders and borrow from online loan platforms to fund their increasing down-payment due to the housing price appreciation.[2] In this regard, the housing restriction policies might have a limited impact on the speculators. This paper investigates household real estate financing behaviors and provides evidence for Chinese regulators to advance their risk management on household leverage.

We are aware that in the credit market, unobservable demand-side factors might be correlated with the supply-side factors. We address this concern by exploiting the regulatory change on the credit supply in the traditional financial market. We adopt the housing policy change on the down payment around 2013 as a natural experiment. In 2013, several metropolitan cities[3] in China announced to increase the required down-payment of the second home purchase from 60 to 65%, further to curb the real estate speculation. The core of policy depends on the household's loan-to-value ratio and property units the household owned, which does not directly correlate with factors and incentives motivating the speculative demand in the residential real estate market. This sudden constraint on credit creates a positive shock to credit demand in shadow banking. Given that individuals can borrow from the

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

[3] The cities that implemented the restriction policy are Beijing, Shanghai, Shenzhen, Guangzhou, Hangzhou, Nanjing, Wuhan, Nanchang, Shenyang, and Changsha.

informal lending platform, we expect the household to use online lending to finance their down payment and lever up their household portfolio.

Our paper contributes to serval strands of literature. First of all, we enrich the literature on shadow banking. Existing literature focus on the securitization products issued by financial intermediaries such as commercial banks and trusts (Acharya et al., 2016; Allen et al., 2019; Chen et al., 2018). Unlike these studies, we investigate another type of shadow banking-online lending, which solely focuses on individual investors instead of financial institutions and corporations. By further examining the pricing determinants, the empirical evidence points out potential systemic risks generated from individual investors and households.

Most importantly, our study is closely related to the growing studies on the impact of FinTech on real estate finance. Most studies on FinTech lending examine how the borrower's demographic characteristics (Ravina, 2012; Pope and Sydnor, 2011; Duarte et al., 2012) and soft information (Herzenstein et al., 2011; Michels, 2012; Lin et al., 2013; Freedman and Ginger, 2017) affect the loan outcomes or the FinTech lender's decision. Our research is the first to examine the role of online lending in relation to household investment and real estate finance. Our paper first shows that households tend to employ online loans to pay for the increasing down-payment and circumvent the regulatory change in both financial and real estate market. The behavior leads to a higher probability of getting a real estate loan, a higher cost of debt, but a higher delinquency rate, evidenced by the moral hazard.

We organize the remainder of the paper as follows. "Literature Review and Hypothesis Development" section reviews the related literature and develops hypotheses. "Data and Sample Construction" section describes the data and sample construction. "Empirical Design" section presents empirical designs. "Empirical Results and Interpretations" section presents empirical results. "Robustness Check" section performs additional analysis and robustness checks. "Policy Implication and Conclusion" section concludes.

Literature Review and Hypothesis Development

Most emerging literature on FinTech lending examine how the borrower's demographic characteristics like appearance and disclosures (Ravina, 2012; Herzenstein et al., 2011; Pope and Sydnor, 2011; Michels, 2012; Duarte et al., 2012) and soft or nonstandard information (Lin et al., 2013; Freedman and Ginger, 2017; Iyer et al., 2016; Herzenstein et al., 2011; Michels, 2012) affect the loan outcomes or the lender's decision in loan originations.

The emergence of shadow banks is also accompanied by the unconventional monetary policy following the financial crisis. Most recent papers document the risk-taking channel through traditional financial institutions (Maddaloni and Peydró, 2011; Jiménez et al., 2014; Dell'Ariccia et al., 2017; Di Maggio and Kacperczyk, 2017). However, the existing theory on risk-taking mechanisms is specific to traditional financial institutions. Previous literature have provided mixed evidence on FinTech lenders compared with the lenders from commercial banks. De Roure et al. (2018) build a theoretical model including both banks and shadow banks. Using the consumer credit data in Germany, they empirically document that P2P lenders in shadow banks are generally riskier than bank borrowers. Using the survey data in China, Liao et al. (2017) report similar findings with online platforms. However, for US consumer credit lending, Wolfe and Yoo (2017) find that households resort to P2P platforms when they are crowded out by small commercial banks.

Meanwhile, the excessive household leverage due to loose credit supply poses excessive individual risk-taking in the real estate market (Gorton & Ordoñez, 2014; Adelino et al., 2016; Mian & Sufi, 2009, 2011; Mian et al., 2015). Buchak et al. (2018) further document that in the residential loan market, less creditworthy borrowers are crowded out by the traditional banks and served by FinTech platforms. But it remains unsolved whether FinTech lenders in the online lending platforms target risky borrowers in the real estate market or not (Fuster et al., 2018). Unlike financial institutions, individual investors face different incentives and constraints (Hildebrand et al., 2016), which might trigger investors herding (Zhang & Liu, 2012) and their risk-taking behavior, especially when there is a negative shock from the mortgage supply. Therefore, we hypothesize that:

Hypothesis 1(A) Shadow banking encourages the risk-taking behavior of individual real estate investors.

Hypothesis 1(B) Shadow bank discourages the risk-taking behavior of individual real estate investors.

Data and Sample Construction

This study uses the loan and listing data of an online lending platform in China from January 2011 to April 2015. We end the sample in April 2015 because of the need to measure the loan performance. Another reason is that the central government forbid online lending platforms from financing the down payment for the home purchase after 2016.[4] As the leading platform in China, the platform offers fixed-rate and unsecured loans. In particular, for a specific online loan request, the borrower files both the loan amount and interest rate when applying online. The online platform revises the loan amount and interest rate according to the borrower's credit profile before listing the loan on the platform. If investors fund 100% of the loan request, the application will be approved. When a loan is in default, the platform hires collection agencies to retrieve the money and returns the collected money to the lenders if any. The loans carry 1% of the remaining balance as the prepayment penalties.

We use the platform for several reasons. First of all, the platform is one of the earliest and largest online platforms in China, launched in 2010. According to an online lending industry index established by the nationwide rating agency,[5] the platform ranks in the top three in our sample period. Second, unlike some lending platforms, the main business

[4] Afterward, to finance the down payment, risky borrowers requested real estate loans from microfinance companies, granted with intermediary licenses.

[5] WDZJ.com.

of the platform is purely online, which could isolate the behavioral bias motivated by the offline private information between borrowers and investors. Finally, the platform has pioneered a standardized practice for the online platform in China, followed by the subsequent small lending platforms. The platform discloses the unique user ID and most comprehensive information of borrowers and lenders for each loan granted compared with other small lending platforms. The platform used in this study represents a typical online loan platform in China and provides a perfect setting for our research.

Empirical Design

To identify whether individual risk-taking affects real estate financing through shadow banking, we use the following models:

$$Y_{it} = \alpha_t + \beta Risk_{it} * RE\ Loan_{it} + \gamma RE\ Loan_{it} + Risk_{it} + Z_{it} + X_t + Fixed\ Effects + \varepsilon_{it} \tag{1}$$

$$Y\_RE_{it} = \alpha_t + \beta Risk_{it} + \gamma Z_{it} + X_t + \text{Fixed Effects} + \varepsilon_{it} \tag{2}$$

We construct several measures of loan outcomes. The measure *Success* equals one if the online loan request gets approved. The measure *Loan Amount* is defined as the loan amount funded. Simultaneously, we use *Success RE*, which equals one if the real estate loan request is supported, and *Loan Amount RE*, defined as the real estate loan amount funded, to measure the outcome. Therefore, in the specifications, Y_{it} is a measure of loan application outcome, which can be either *Success* or *Loan Amount*, and Y_RE_{it} is a measure of real estate loan application outcome, which can be either *Success RE* or *Loan Amount RE*.

We use *Credit Grade* to measure the borrower risk. The platform reports the credit grade rating in different-sized bins as AA、A、B、C、D、E、and HR, in which AA denotes loan applications with the highest credit rating, and HR denotes loan applications with the lowest credit rating. We transform them to numerical values from 1 to 7, in which 1 denotes online loan applications with the lowest credit risk, and 7 denotes online loan applications with the highest credit risk. In Appendix Table 12, we show the relationship between the risk rating measures and borrower characteristics. We document a higher credit risk is associated with a younger single person who has a lower education level, a lower income level, car ownership, and homeownership. Borrowers are required to submit their national ID, education degree, income statement, employment letter, and credit record for verification, which determines borrowers' credit rating as shown in Appendix Table 12.

In the specifications, α_t is time fixed effects (year-month), $Risk_{it}$ is either *Credit Grade* or *Yield*. Z_{it} is a set of control variables, including both loan level and borrower level characteristics. Following the existing literature, we include *Return* and *Maturity* to control loan characteristics. *Return* is the expected return of the loan, which equals promised lender yield minus expected loss and the expected loss is calculated based on the past default rate. *Maturity* is the loan listing term in months.

To control individual characteristics, we include *Monthly Income, Age, Married, Education, Homeowner, and Car owner. Monthly Income* is defined as borrower's monthly income level measured in RMB, in which one represents 0–1000, two represents 1000–2000, three represents 2000–5000, four represents 5000–10,000,five represents 10,000–20,000,six represents 20,000–50,000, and seven represents 50,000 and above. *Age* is the age of the borrower. *Married* is a dummy variable describing the marital status of the borrower, which equals one if the borrower is married. Education is borrower's education level, which defines one for high school and below, two for college, three for undergraduate, and four for graduate and above. *Homeowner* is a dummy variable that equals one if the borrower is a homeowner and zero otherwise. *Car owner* is a dummy variable that equals one if the borrower is a car owner and zero otherwise. The Appendix Table 11 lists all variables used in this paper's empirical analyses.

Furthermore, we include macroeconomic variables X_t to address and mitigate the concern that other macroeconomic factors may co-drive the effect. In different specifications we include city fixed effects. Under Eq. (1),β and γ capture the impact of real estate loans on shadow banking. Under Eq. (2),β captures the effect of risk-taking on real estate investment. If the banking sector crowds out risky real estate borrowers, and shadow banking encourages individual risk-taking behavior, β should be positive. Under both specifications, standard errors are clustered by city.

We are aware that macro and housing market policies might change the applicant structure over time. We partially address the concerns by controlling the time fixed effect in the robustness check. In Fig. 2, we plot the credit grade of the applicants over the study period. Figure 2 depicts that applicant structure does not vary around the regulatory change in 2013.

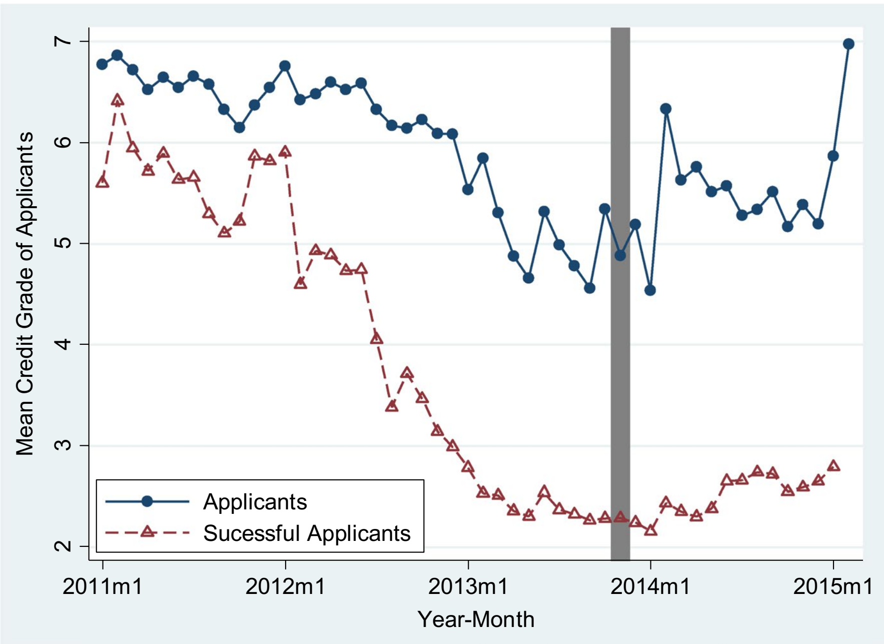

Fig. 2 Mean Credit Grade of Applicants

More importantly, we perform a Difference-in-Difference analysis that exploits a market regulatory change conducted in 2013. The regulatory change in 2013 requires the minimum down payment ratio to be 65% instead of 60% for a second-home purchase. The core of this housing restriction policy depends on the loan-to-value ratio and property units the household owned, which does not directly correlate with factors and incentives motivating the speculative demand in the residential real estate market. Unlike other monetary and fiscal policies, this sudden constraint on credit creates a positive shock to credit demand in shadow banking. Given that individuals can borrow from the informal lending platform, we expect the household to use online lending to finance their down payment and lever up their household portfolio. We construct a dummy variable, *Policy*, defined as one if the period fall in the policy time window and zero otherwise. We analyze the impact of the housing policy on individual risk-taking using following specifications:

$$Y\_RE_{it} = \alpha_t + \beta_1 Policy + \beta_2 Policy \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + X_t + \text{Fixed Effect} + \varepsilon_{it} \tag{3}$$

$$Return_{it} = \alpha_t + \beta_1 \text{Policy} + \beta_2 Policy \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + X_t + \text{Fixed Effect} + \varepsilon_{it} \tag{4}$$

where Y_RE_{it} is a measure of real estate loan application outcome, which can be either *Success RE* or the natural logarithm of real estate loan funded, and $Return_{it}$ is the estimated return. α_t is time fixed effects (year-month), $Risk_{it}$ is either *Credit Grade* or *Yield*, Z_{it} is control variables including both loan level and borrower level characteristics. We further include macroeconomic variables X_t to mitigate the concern that other macroeconomic factors may drive the effect. We also include city fixed effects. Under Eq. (3), the β's capture the economic impact of the housing policy. If the housing policy deters real estate speculation, we expect the β's to be negative. Under Eq. (4), the β's should be positive if the housing policy drives up the cost of debt.

To examine the impact on ex-post loan performance, we define the dependent variable *Default* as the 30+days delinquency and loss to be consistent with the bad debt definition in the platform. *Default* is defined as one if the loan is in default or even bad debt and equals zero otherwise. Specifically, we estimate the following specifications on all approved loans,

$$D_{it} = \alpha_t + \beta Risk_{it} + \gamma Z_{it} + X_t + \text{Fixed Effect} + \varepsilon_{it} \tag{5}$$

where D_{it} is variable *Default* for loan *i* issued at time *t*. We perform the Difference-in-Difference approach to mitigate the endogenous issue and concerns for sample bias.

Empirical Results and Interpretations

This section presents the empirical results. Overall, our findings support that shadow banking encourages individual risk-taking in real estate finance.

Table 1 Summary Statistics

	Number of Observations	Mean	S.D	P25	P50	P75
Full Sample						
Success	287,228	0.33	0.47	0	0	1
Success RE	287,228	0.001	0.03	0	0	0
Loan Amount (RMB)	287,228	61,102.12	92,244.34	10,000	40,000	70,000
Loan Amount RE (RMB)	4987	94,537.62	109,944.8	30,000	50,000	100,000
Loan Amount (in logarithm)	287,228	10.31	1.27	9.21	10.6	11.16
Loan Amount RE (in logarithm)	287,228	0.19	1.44	0	0	0
Default	287,228	0.003	0.06	0	0	0
Credit Grade	287,228	5.6	2.23	2	7	7
Return(%)	287,228	14.11	3.26	12	13	15
Maturity(month)	287,228	18.26	11.12	9	18	24
Monthly Income(in logarithm)	287,228	4.08	1.26	3	4	5
Homeowner	287,228	0.43	0.5	0	0	1
Car owner	287,228	0.02	0.15	0	0	0
Education	287,228	1.84	0.77	1	2	2
Age	287,228	32.1	7.77	26	30	36
Married	287,228	0.56	0.5	0	1	1
Subsample of Loans Granted						
Success RE	93,466	0.003	0.06	0	0	0
Loan Amount (RMB)	93,466	53,829.05	57,265.64	27,500	47,100	77,800
Loan Amount RE (RMB)	325	17,475.69	20,831.45	8000	13,000	20,000
Loan Amount (in logarithm)	93,466	10.55	0.96	10.22	10.76	11.26
Loan Amount RE (in logarithm)	93,466	0.03	0.56	0	0	0
Default	93,466	0.01	0.1	0	0	0
Credit Grade	93,466	2.77	1.76	2	2	2
Return(%)	93,466	12.97	1.97	12	13	13.2
Maturity(month)	93,466	24.18	11.39	18	24	36
Monthly Income(in logarithm)	93,466	4.47	1.28	3	4	5
Homeowner	93,466	0.48	0.5	0	0	1
Car owner	93,466	0.05	0.2	0	0	0
Education	93,466	1.97	0.74	1	2	2
Age	93,466	36.23	8.43	29	35	42
Married	93,466	0.71	0.45	0	1	1

This table presents descriptive statistics for variables used in the paper

Summary Statistics

Table 1 presents the summary statistics. In the full sample, about 1.7% of the loan requests are real estate loans, and about 32.5% of all loan requests are funded. The loan amount

Table 2 Loan Type, Loan Characteristics and Housing Policy

Panel A: Full Sample			
	Non-Real Estate Loans	Real Estate Loans	T-stats
Credit Grade	5.57	6.91	-42.3***
Age	32.12	31.1	9.19***
Married	0.56	0.53	3.31***
Education	1.84	1.98	-12.71***
Income	4.08	3.78	17.16***
Car	0.02	0.01	5.52***
Homeowner	0.43	0.37	9.13***
Yield	14.1	14.27	-3.47***
Maturity	18.21	20.95	-17.27***
Panel B: Subsample of Loans Granted			
	Non-Real Estate Loans	Real Estate Loans	T-stats
Credit Grade	2.76	6.12	-34.55***
Age	36.24	32.9	7.15***
Married	0.71	0.59	4.75***
Education	1.97	2.27	-7.32***
Income	4.48	3.74	10.46***
Car	0.05	0.07	-2.36***
Homeowner	0.48	0.42	2.06***
Yield	12.97	13.15	-1.69**
Maturity	24.21	14.64	15.15***
Panel C: Subsample of Real Estate Loans (all RE applications)			
	Prior Policy	Post Policy	T-stats
Credit Grade	6.91	6.94	-0.99
Age	31.29	29.67	5.45***
Married	0.55	0.42	5.74***
Education	1.94	2.30	-10.18***
Income	3.73	4.09	-7.75***
Car	0.01	0.00	1.91*
Homeowner	0.38	0.25	6.24***
Yield	14.39	13.3	8.75***
Maturity	21.23	18.89	5.41***

requested is on average, around 60,000 RMB (equivalent to $9,375), and the average loan term is 18 months, that is, one and half years. The average *Credit Grade* is 5.6, indicating a comparably high credit risk associated with the loans. On average, 42.9% of applicants are homeowners, while 2.3% are car owners. The average estimated return is 14%, in contrast with the 5% base interest rate offered by the People's Bank of China.

Before we perform the formal analysis, we present univariate results on the characteristics of the online loan. We first split the sample into real estate loans and non-real estate loans. Table 2 shows the results. It is evident from Table 2 Panel A and Panel B that real estate loans are much riskier (higher credit risk) associated with higher yield and longer maturity. Loan applicants for home purchase appear to be

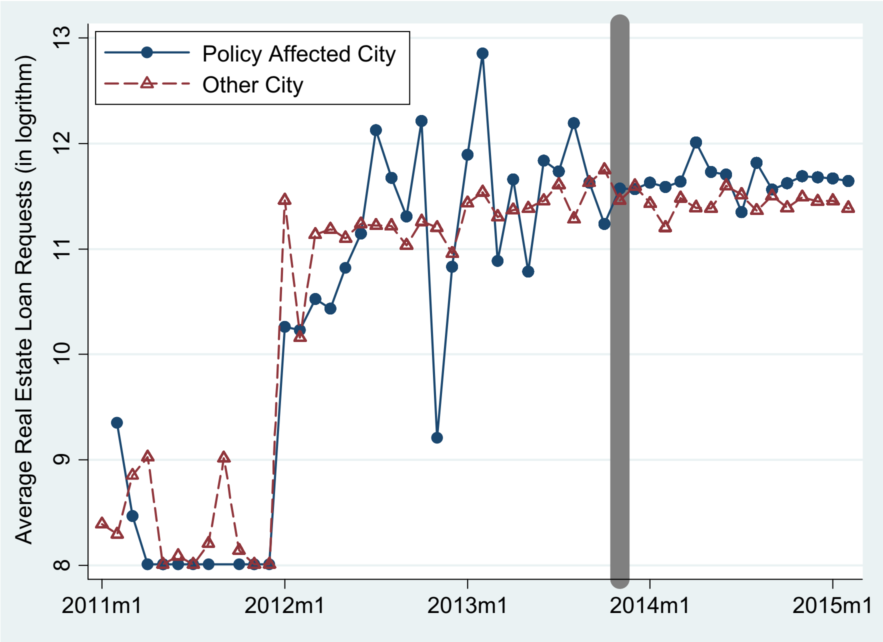

Fig. 3 Real Estate Loan Requests and Housing Policy

younger, less likely to be married with a comparably lower income level, another indicator for higher credit risk. We further separate the sample period into *the non-Policy* period and *Policy* period, then compare the characteristics of real estate loans around the policy implementation. We show the results in Table 2 Panel C, where after the policy is implemented, real estate loan applicants exhibit a higher risk with lower homeownership.

To pin down the regional effect of housing restriction policy, we also calculate the real estate loan requests over the policy period for different cities. Figure 3 shows that the loan amount of affected cities is much higher during the policy period than the unaffected cities.

Real Estate Finance and Risk-Taking

We first show the results estimating Eq. (1) using *Credit Grade* as the risk measure in Table 3. We include almost all loan and borrower characteristics reported by the platform in the regression. The first three columns of Table 3 document results using *Success* as the dependent variable in the regression. To control both location-specific and time-invariant demand factors, we include both time (year-month) and city fixed effects in the specifications. For the full sample analysis, we document that coefficients on *Credit Grade* are statistically significant and negative, indicating that safer loan requests are more likely to be approved, which is similar with

Table 3 Real Estate Loan and Online Lending

	Success			Loan Amount		
Credit Grade	-0.1824***		-0.1825***	-1.9520***		-1.9520***
	(0.0014)		(0.0014)	(0.0161)		(0.0161)
RE Loan		0.7101***	0.1001***		6.6829***	0.8188***
		(0.1190)	(0.0170)		(1.2484)	(0.1594)
Credit Grade *RE Loan		-0.1263***			-1.2267***	
		(0.0167)			(0.1750)	
Yield *RE Loan			-0.0069***			-0.0602***
			(0.0011)			(0.0100)
Yield	0.0011***	-0.0286***	0.0011***	0.0029	-0.3140***	0.0037
	(0.0004)	(0.0022)	(0.0004)	(0.0035)	(0.0231)	(0.0035)
Maturity	-0.0010***	0.0105***	-0.0010***	-0.0016	0.1205***	-0.0016
	(0.0001)	(0.0010)	(0.0001)	(0.0013)	(0.0112)	(0.0014)
Age	0.0016***	0.0111***	0.0016***	0.0188***	0.1204***	0.0188***
	(0.0001)	(0.0005)	(0.0001)	(0.0016)	(0.0051)	(0.0016)
Married	0.0078***	0.0636***	0.0078***	0.0522***	0.6488***	0.0524***
	(0.0013)	(0.0041)	(0.0013)	(0.0133)	(0.0435)	(0.0133)
Education	0.0101***	0.0255***	0.0101***	0.0700***	0.2350***	0.0702***
	(0.0013)	(0.0038)	(0.0013)	(0.0128)	(0.0401)	(0.0128)
Income	0.0043***	0.0259***	0.0044***	0.0966***	0.3276***	0.0966***
	(0.0009)	(0.0025)	(0.0009)	(0.0091)	(0.0267)	(0.0091)
Car owner	0.1565***	0.3243***	0.1565***	1.2518***	3.0479***	1.2522***
	(0.0173)	(0.0174)	(0.0173)	(0.2271)	(0.2059)	(0.2270)
Homeowner	-0.0023	-0.0414***	-0.0024	0.0219	-0.3967***	0.0213
	(0.0018)	(0.0086)	(0.0018)	(0.0250)	(0.0928)	(0.0250)
Population	-0.0255	-0.2148	-0.0246	-0.3613	-2.3886	-0.3557
	(0.0291)	(0.1556)	(0.0291)	(0.3423)	(1.7295)	(0.3425)
GDP	-0.0078	-0.0211	-0.0077	0.0008	-0.1417	0.0012
	(0.0058)	(0.0208)	(0.0058)	(0.0726)	(0.2407)	(0.0727)
Constant	1.4584***	1.5487	1.4503***	15.1780***	16.1585	15.1221***
	(0.2125)	(1.1063)	(0.2124)	(2.4946)	(12.3112)	(2.4963)
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	287,228	287,228	287,228	287,228	287,228	287,228
Adjusted R2	0.7952	0.4672	0.7952	0.8344	0.5012	0.8344

This table presents the results of estimating $Y_{it} = \alpha_t + \beta Risk_{it} * REloan_{it} + \gamma Z_{it} + X_t + \text{FixedEffects} + \varepsilon_{it}$. The dependent variable is *Success* in Columns (1)-(3), and the dependent variable is the loan amount funded (in logarithm) in Columns (4)-(6). Clustered standard errors are presented in parentheses. *** denotes the significance at 1%, ** denotes the significance at 5%, *denotes the significance at 10%, respectively banks. Likewise, loan applications with higher yields and shorter maturity are more likely to get approved. For control variables, the coefficients for *Age, Married, Education, Income,* and *Car owner* are positively significant, indicating that less risky borrowers are more likely to get funded. This result is in a line with the risk aversion for individual investors. In column (2) and column (3), we include *REloan* into the regression. The coefficients on *RE loan*s are significantly positive, indicating that real estate loan requests are more likely to be approved. Given the statistics in Table 2 that real estate loans are riskier in general, the results on real estate loans are counterfactual. Moreover, for the interaction terms of *RE loan* and *Credit Grade*, we document a smaller though negative sign on the interaction terms, indicating differences of real estate loans in the shadow banking business. Columns (4—(6) show the results using *Loan Amount* as the dependent variable in the regression, where results are quantitatively similar.

In Table 4, we show the results of estimating Eq. (2) using *Credit Grade* as the risk measure. The first four columns show results using *Success RE* as the dependent variable in the regression. The coefficient estimates on *Credit Grade* are significantly positive, indicating that riskier loan requests are more likely to be approved if the application is a real estate loan application. Therefore, the result supports the hypothesis that shadow banking inspires individual risk-taking in real estate investment. As we apply both probit and panel pooled regressions to estimate coefficient in Columns (1)—(4), the probability of approving a riskier real estate loan is 0.7% higher compared with the probability of getting a safer real estate loan approved. Considering that only around 32% of loan applications are eventually approved, the economic magnitude of the effect is significant and large. Columns (5)—(6) show the results using *Loan Amount RE* as the dependent variable in the regression. The coefficient estimates on *Credit Grade* are again significantly positive, consistent with the hypothesis. Given that rational investors are risk-averse and real estate loans account for a very limited portion of all loan requests, the evidence that riskier real estate loans are more likely to get funded does not necessarily mean that investors are taking the same level of risk. This is because each of the lenders only contributes a small portion of the specific real estate loan, and they invest in many other projects to diversify the risk simultaneously. In other words, individual real estate loans are risky, but the lender's portfolio is not as much as evidence in Table 3.

As for the control variables, we document that income and homeowners are significant and negative, in contrast with the positive sign for all loan types in Table 3. The riskier (higher credit risk) borrowers associated with lower income and homeownership, who cannot secure the mortgage from the traditional financial institutions, are more likely to get funded if they apply for the real estate loan in the online platform. Under Eq. (2),β captures the effect of risk-taking on real estate investment. If the banking sector crowds out risky real estate borrowers, and shadow banking encourages individual risk-taking in real estate lending, β should be positive. The coefficient of variable *Yield* is negative conditioned on the positive sign of *Risk*, which suggests that shadow banking encourages individual risk-taking in real estate finance. Compared with other loans, riskier real estate loans have access to more funding in shadow banking, consistent with the crowding-out effect of financial institutions (Wolfe & Yoo, 2017).

Table 4 Risk Taking and Real Estate Loan

	Success RE				Loan Amount RE	
	Full sample		Subsample of Loans Granted		Full sample	Subsample of Loans Granted
Credit Grade	0.007***	0.289***	0.004***	0.232***	0.078***	0.038***
	(0.000)	(0.013)	(0.000)	(0.019)	(0.004)	(0.004)
Yield	-0.001***	-0.018***	-0.001***	-0.019	-0.007***	-0.008***
	(0.000)	(0.003)	(0.000)	(0.012)	(0.001)	(0.002)
Maturity	0.001***	0.022***	0.000**	-0.002	0.012***	0.001**
	(0.000)	(0.001)	(0.000)	(0.003)	(0.001)	(0.000)
Age	0.000***	0.008***	0.000	0.003	0.003***	0.000
	(0.000)	(0.001)	(0.000)	(0.003)	(0.001)	(0.000)
Married	0.003***	0.076***	-0.000	0.010	0.035***	-0.004
	(0.001)	(0.017)	(0.001)	(0.056)	(0.008)	(0.005)
Education	0.006***	0.143***	0.002***	0.185***	0.065***	0.018***
	(0.001)	(0.013)	(0.000)	(0.035)	(0.007)	(0.004)
Income	-0.001***	-0.052***	-0.001***	-0.130***	-0.011***	-0.009***
	(0.000)	(0.007)	(0.000)	(0.022)	(0.003)	(0.002)
Car owner	0.008***	0.040	0.001	0.101	0.086***	0.008
	(0.002)	(0.072)	(0.002)	(0.104)	(0.018)	(0.017)
Homeowner	-0.011***	-0.189***	-0.002**	-0.176***	-0.118***	-0.016**
	(0.001)	(0.019)	(0.001)	(0.058)	(0.011)	(0.007)
Population	-0.033*	0.049*	-0.011	0.007	-0.369*	-0.098
	(0.018)	(0.026)	(0.012)	(0.070)	(0.191)	(0.105)
GDP	-0.009**	-0.094***	-0.034***	-0.170***	-0.098**	-0.308***
	(0.004)	(0.015)	(0.009)	(0.043)	(0.038)	(0.076)
Constant	0.272**	-4.457***	0.414***	-1.904***	2.978**	3.757***
	(0.129)	(0.249)	(0.112)	(0.590)	(1.398)	(1.009)
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes		Yes		Yes	Yes
Observations	287,228	287,228	93,466	93,466	287,228	93,466
Adjusted R^2	0.02		0.05		0.02	0.04
Pseudo R^2		0.11		0.25		

This table presents the results of estimating $Y\_RE_{it} = \alpha_t + \beta Risk_{it} + \gamma Z_{it} + X_t + \text{FixedEffects} + \varepsilon_{it}$. The dependent variable is *Success RE* in Columns (1)-(4), and the dependent variable is the real estate loan funded (in logarithm) in Columns (5)-(7). Clustered standard errors are presented in parentheses. *** denotes the significance at 1%, ** denotes the significance at 5%, *denotes the significance at 10%, respectively

To ensure the results are robust to alternative risk measures, we employ interaction terms as the risk measure. Homeownership can serve as an alternative implicit guarantee for the loan. Similar to the above results, the coefficient estimates on $Yield \times Credit\ Grade$ and $Homeowner \times Credit\ Grade$ are significantly negative, indicating that loan requests from less creditworthy borrowers are more likely to get funded. When the traditional banks crowd out less creditworthy borrowers, it does induce the risker households to circumvent the market regulation by borrowing from FinTech platforms (Buchak et al., 2018; Wolfe & Yoo, 2017). Moreover, unlike financial institutions, individual investors on FinTech platforms face different incentives and constraints (Hildebrand et al., 2016), which might trigger investors herding (Zhang & Liu, 2012) and their risk-taking behavior, especially when there is a negative shock from the mortgage supply.

In unreported analysis, we examine whether individual investors invest in real estate loans conditional on risk measures by comparing loan requests with the identical credit risk level during the same month. The results are still consistent. We further include *City-month FEs,* instead of *city FEs* and *month FEs* for Table 3–5 in the robustness check. The results with city-month FE are quantitatively similar to the main results.

Overall, results in Table 4 and Table 5 suggest that in contrast with traditional financial institutions, the shadow banking sector takes more risk and serves as the alternative financing for riskier real estate loans.

Housing Policy on Risk Taking

We recognize that a potential problem with baseline results is that after 2010 the Chinese government started to impose several rounds of market regulation to deter speculation in the housing market.,[6] mainly targeting traditional financial intermediaries. To the extent that the crowding-out effect of financial institutions (Wolfe & Yoo, 2017) affects individual risk-taking in shadow banks, the stringent market regulation should also affect individual risk-taking in real estate investment. As such, we examine how the market regulation affects online investors' risk-taking in real estate investment. Table 6 presents the results of estimating Eq. (3). Consistent with the conjecture that tighter market regulation deters the speculation, the coefficient on *Policy* is significantly negative. Interestingly, the coefficients on interaction terms between the housing policy and risk measures are significantly positive. The existence of online loans attracts a lot of lower-quality borrowers and speculators. It suggests that while the market regulation deters real estate speculation in general, it does induce the second-home buyer to circumvent the market regulation by borrowing from online lending platforms. Compared with non-homeowners, second-home buyers can use their first home as an implicit guarantee in online lending to receive more funding. Given that online loans typically mature in a very short period and carry interest

[6] For example, on February 21 and April 30, 2010, the residential property purchase limits policy in Beijing is considered as "the harshest regulation in the housing market". The housing policy limits the household with a Beijing Hukou to hold two residential properties at maximum and prohibits the household without a Beijing Hukou from home purchases. The policy on the first home purchase requires a 30% down payment at least for a residential property larger than 90 m^2 in size. The following policy on the second home purchase is a 50% down payment at least with a mortgage rate of a minimum of 10% above the base rate.

Table 5 Risk-Taking, Loan Characteristics, and Real Estate Loan

	The subsample of Loans Granted			
	Success RE	Loan Amount RE	Success RE	Loan Amount RE
Credit Grade	0.010***	0.091***	0.005***	0.044***
	(0.001)	(0.014)	(0.001)	(0.005)
Credit Grade* Yield	-0.001***	-0.004***		
	(0.000)	(0.001)		
Homeowner	-0.002**	-0.018***	0.003**	0.027**
	(0.001)	(0.007)	(0.001)	(0.011)
Credit Grade* Homeowner			-0.001***	-0.015***
			(0.001)	(0.005)
Yield	0.002**	0.017**	-0.001***	-0.008***
	(0.001)	(0.007)	(0.000)	(0.002)
Maturity	-0.000	0.000	0.000*	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.000	-0.004	-0.000	-0.002
	(0.001)	(0.005)	(0.001)	(0.005)
Education	0.002***	0.018***	0.002***	0.019***
	(0.000)	(0.004)	(0.000)	(0.004)
Income	-0.001***	-0.008***	-0.001***	-0.009***
	(0.000)	(0.002)	(0.000)	(0.002)
Car owner	-0.000	-0.000	0.001	0.007
	(0.002)	(0.017)	(0.002)	(0.017)
Population	-0.010	-0.082	-0.009	-0.078
	(0.011)	(0.103)	(0.011)	(0.104)
GDP	-0.034***	-0.309***	-0.033***	-0.306***
	(0.009)	(0.075)	(0.009)	(0.076)
Constant	0.371***	3.352***	0.396***	3.578***
	(0.109)	(0.985)	(0.111)	(1.001)
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Observations	93,466	93,466	93,466	93,466
Adjusted R^2	0.045	0.045	0.045	0.045

This table presents the results of estimating $Y\_RE_{it} = \alpha_t + \beta Risk_{it} + \gamma Z_{it} + X_t + \text{FixedEffects} + \varepsilon_{it}$. The dependent variable is *Success RE* in Columns (1) and (3), and the dependent variable is the real estate loan funded (in logarithm) in Columns (2) and (4). Clustered standard errors are presented in parentheses. *** denotes the significance at 1%, ** denotes the significance at 5%, *denotes the significance at 10%, respectively

rates of at least 10%, the future cash flow for these lower-quality borrowers is uncertain and underestimated. The results are consistent with the more prominent effects shown in Table 4 and Table 5.

Table 6 The Housing Policy on Real Estate Loan

	(1) Full sample	(2)	(3) The subsample of Loans Granted	(4)
	Success RE	Loan Amount RE	Success RE	Loan Amount RE
Policy	-0.005***	-0.055***	-0.003**	-0.027**
	(0.002)	(0.018)	(0.001)	(0.010)
Homeowner* Credit Grade	-0.002***	-0.019***	-0.001***	-0.010***
	(0.000)	(0.002)	(0.000)	(0.003)
Policy * Homeowner* Credit Grade	0.001*	0.006*	0.001*	0.010**
	(0.000)	(0.004)	(0.001)	(0.005)
Credit Grade	0.008***	0.086***	0.004***	0.042***
	(0.000)	(0.004)	(0.000)	(0.005)
Yield	-0.001***	-0.007***	-0.001***	-0.008***
	(0.000)	(0.001)	(0.000)	(0.002)
Maturity	0.001***	0.012***	0.000**	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
Age	0.000***	0.003***	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Married	0.003***	0.036***	-0.000	-0.002
	(0.001)	(0.008)	(0.001)	(0.005)
Education	0.006***	0.065***	0.002***	0.019***
	(0.001)	(0.007)	(0.000)	(0.004)
Income	-0.001***	-0.011***	-0.001***	-0.008***
	(0.000)	(0.003)	(0.000)	(0.002)
Car owner	0.007***	0.072***	0.001	0.012
	(0.002)	(0.018)	(0.002)	(0.017)
Population	-0.022	-0.251	-0.007	-0.057
	(0.019)	(0.208)	(0.013)	(0.117)
GDP	-0.009**	-0.096**	-0.033***	-0.301***
	(0.004)	(0.038)	(0.009)	(0.079)
Constant	0.193	2.102	0.377***	3.397***
	(0.141)	(1.519)	(0.120)	(1.088)
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Observations	287,228	287,228	93,466	93,466
Adjusted R^2	0.020	0.021	0.045	0.045

The table reports the results of estimating $Y_{it} = \alpha_t + \beta_1 Policy + \beta_2 Policy \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + X_t + \text{Fixed Effects} + \varepsilon_{it}$, where Policy is the indicator for the implementation of the housing policy, which requires the minimum down payment ratio to be 65% instead of 60% for a second home in 2013. Risk is measured by *Credit Grade* and *Homeownership*. The dependent variable is *Success RE* in Columns (1)—(2), and the dependent variable is the real estate loan funded (in logarithm) in Columns (3)—(4). Clustered standard errors are presented in parentheses. *** denotes the significance at 1%, ** denotes the significance at 5%, *denotes the significance at 10%, respectively

Table 7 shows the results of estimating Eq. (4). The coefficient on *Policy* is all positive and mostly significant, indicating that loan applications with higher estimated returns are more likely to get funded during the housing restriction policy period. The coefficient estimates on interaction terms between the housing policy and risk measures are negative and statistically significant. Given that online loans typically mature in a very short period and carry interest rates of at least 10%, the future cash flow for these high risky homeowners who try to speculate the housing market is uncertain and underestimated. The results further suggest that the unconventional regulatory change in the real estate market does encourage individual investors to fund riskier real estate loans with higher expected returns in the shadow banking sector.

Risk Taking and ex Post Loan Performance

Finally, we present results on the loan performance. The results of estimating Eq. (5) are shown in Table 8, with Columns (1) using *Credit Grade* as the risk measure and Columns (2) using *Real Estate Loan* as the risk measure. The coefficient estimates of β are all significantly positive, indicating that riskier loans, especially real estate loans, have higher default rates ex-post. The result holds even when holding all other characteristics constant. A one-degree reduction in *Credit Grade* can lead to a 1.8% percentage point increase in default probability, and real estate loans are 2.1% higher in default probability.

Table 9 presents the results, with Columns (1) using *Credit Grade* as the risk measure and Columns (2) using *Credit Grade* and *Homeowner* as the risk measure. The coefficient estimates for *Policy* are all statistically significant and positive, indicating that loans originated during the housing market regulation have higher ex-post default rates as evidence of the crowding-out effect from traditional financial intermediaries (Wolfe & Yoo, 2017). From Column (1), the economic magnitude of policy on ex-post default is 1.1% and significant. Meanwhile, the implementation of the housing policy does deter real estate speculation, evidenced by the negative and significant signs on interaction terms. We also try categorizing those in delinquency in robustness check and still find similar results.

Robustness Check

Subsample Analysis

In above results, we pool together all the loan requests in all periods. The subsection examines the effect of risk-taking and housing policies using different periods, including the pre-policy and post-policy periods. The results are quantitatively similar.

Regional Disparity

Considering that China's financial and real estate markets are segmented and unbalanced, we further analyze whether there exists the effect of regional heterogeneity.

Table 7 Effect of Home Restriction Policy on Reaching-for-Yield

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample			The subsample of Loans Granted		
Policy		0.54***	0.09		0.49***	0.01
		(0.19)	(0.08)		(0.08)	(0.07)
Policy * Credit Grade		-0.09***			-0.21***	
		(0.03)			(0.03)	
Policy * Homeowner*Credit Grade			-0.02***			-0.03**
			(0.01)			(0.02)
Homeowner*Credit Grade	-0.09***		-0.09***	-0.05***		-0.05***
	(0.01)		(0.01)	(0.02)		(0.02)
Homeowner	0.57***	0.09***	0.58***	0.06	-0.08***	0.07
	(0.07)	(0.02)	(0.07)	(0.06)	(0.03)	(0.06)
Credit Grade	0.59***	0.57***	0.59***	0.48***	0.49***	0.48***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)
Maturity	0.05***	0.05***	0.05***	0.08***	0.08***	0.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	-0.00***	-0.00***	-0.00***	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Married	-0.10***	-0.12***	-0.10***	-0.10***	-0.11***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Education	-0.13***	-0.14***	-0.13***	-0.12***	-0.12***	-0.12***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Income	0.02*	0.02	0.02*	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Car owner	-0.37***	-0.29**	-0.37***	-0.68***	-0.66***	-0.68***
	(0.13)	(0.13)	(0.12)	(0.22)	(0.21)	(0.22)
Population	-1.94***	-1.83***	-2.10***	-2.54***	-2.08***	-2.53***
	(0.66)	(0.62)	(0.70)	(0.78)	(0.59)	(0.75)
GDP	0.09	0.10	0.09	0.70	0.70	0.71
	(0.08)	(0.08)	(0.08)	(0.59)	(0.58)	(0.59)
Constant	20.95***	20.26***	22.07***	27.48***	24.19***	27.32***
	(4.66)	(4.35)	(4.93)	(7.08)	(5.93)	(6.89)
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	287,228	287,228	287,228	93,466	93,466	93,466
Adjusted R^2	0.31	0.31	0.31	0.58	0.58	0.58

The table reports the results of estimating $Y_{it} = \alpha_t + \beta_1 Policy + \beta_2 Policy \times Risk_{it} + \delta Risk_{it} + \gamma Z_{it} + X_t + \text{Fixed Effects} + \varepsilon_{it}$, where *Policy* is the indicator for the implementation of the housing policy, which requires the minimum down payment ratio to be 65% instead of 60% for a second home in 2013. *Risk* is measured by *Credit Grade* and *Homeowner*. Clustered standard errors are presented in parentheses. *** denotes the significance at 1%, ** denotes the significance at 5%, *denotes the significance at 10%, respectively

Table 8 Risk Taking and Ex Post Loan Default

	Default Granted Sample (1)	Default Granted Sample (2)
Credit Grade	0.018***	
	(0.001)	
RE Loan		0.021*
		(0.012)
Yield	0.001	0.006***
	(0.001)	(0.001)
Maturity	0.001***	-0.001***
	(0.000)	(0.000)
Age	0.001***	-0.001*
	(0.000)	(0.000)
Married	0.001	-0.002***
	(0.001)	(0.001)
Education	-0.003***	-0.004***
	(0.001)	(0.001)
Income	0.002***	0.001**
	(0.001)	(0.000)
Car owner	0.020***	0.014***
	(0.004)	(0.004)
Homeowner	-0.003**	0.003**
	(0.001)	(0.001)
Population	-0.015	-0.003
	(0.027)	(0.024)
GDP	0.017	0.013
	(0.011)	(0.012)
Constant	-0.110	-0.156
	(0.207)	(0.191)
Year-Month Fixed Effects	Yes	Yes
City Fixed Effects	Yes	Yes
Observations	93,466	93,466
Adjusted R^2	0.093	0.057

This table presents the results of estimating $D_{it} = \alpha_t + \beta Risk_{it} + \gamma Z_{it} + X_t + \text{FixedEffects} + \varepsilon_{it}$. The dependent variable is *Default*. The risk measure is *Credit Grade*. *Policy* is the indicator for implementing the housing policy, which requires the minimum down payment ratio to be 65% instead of 60% for a second home in 2013. Clustered standard errors are presented in parentheses. *** denotes the significance at 1%, ** denotes the significance at 5%, *denotes the significance at 10%, respectively

Table 10 presents the results. Column (1)—(4) document that homeowners in first-tier cities are more likely to use online lending for home purchases and down payments. The implementation of the housing restriction policy crowds out the financially constrained homeowners and further amplifies the effect. Take Shenzhen as

Table 9 Risk Taking and Ex Post Loan Default

	Default Granted Sample (1)	Default Granted Sample (2)
Policy	0.011***	0.004*
	(0.004)	(0.002)
Policy *Credit Grade	-0.004***	
	(0.001)	
Policy *Homeowner*Credit Grade		-0.003**
		(0.001)
Homeowner*Credit Grade		0.001
		(0.001)
Credit Grade	0.018***	0.017***
	(0.001)	(0.001)
Yield	0.000	0.000
	(0.001)	(0.001)
Maturity	0.000***	0.000***
	(0.000)	(0.000)
Age	0.000***	0.000***
	(0.000)	(0.000)
Married	0.001	0.001
	(0.001)	(0.001)
Education	-0.003***	-0.003***
	(0.001)	(0.001)
Income	0.002***	0.002***
	(0.001)	(0.000)
Car owner	0.021***	0.020***
	(0.004)	(0.004)
Homeowner	-0.003**	-0.004
	(0.001)	(0.003)
Population	-0.008	-0.021
	(0.028)	(0.027)
GDP	0.017	0.017
	(0.011)	(0.011)
Constant	-0.155	-0.065
	(0.220)	(0.211)
Year-Month Fixed Effects	Yes	Yes
City Fixed Effects	Yes	Yes
Observations	93,466	93,466
Adjusted R^2	0.093	0.093

This table presents the results of estimating $D_{it} = \alpha_t + \beta Policy \times Risk_{it} + \beta Risk_{it} + \gamma Z_{it} + X_t + \text{FixedEffects} + \varepsilon_{it}$. The dependent variable is *Default*. The risk measure is *Credit Grade* and *Homeowner*. *Policy* is the indicator for implementing the housing policy, which requires the minimum down payment ratio to be 65% instead of 60% for a second home in 2013. Clustered standard errors are presented in parentheses. *** denotes the significance at 1%, ** denotes the significance at 5%, *denotes the significance at 10%, respectively

Table 10 Regional Heterogeneity

	(1) Success RE Full sample	(2) Success RE Subsample of the loans granted	(3) Loan Amount RE Full Sample	(4) Loan Amount RE Subsample of the loans granted
Policy	-0.006***	-0.001	-0.067***	-0.012
	(0.002)	(0.001)	(0.024)	(0.011)
Policy*Tier1	0.006**	-0.001	0.067**	-0.009
	(0.003)	(0.001)	(0.027)	(0.009)
Policy*Tier1*Homeowner	-0.010***	-0.003	-0.104***	-0.019
	(0.002)	(0.003)	(0.019)	(0.020)
Tier1*Homeowner	0.016***	0.007***	0.170***	0.057***
	(0.002)	(0.002)	(0.022)	(0.015)
Credit Grade	0.007***	0.004***	0.078***	0.038***
	(0.000)	(0.000)	(0.004)	(0.004)
Yield	-0.001***	-0.001***	-0.007***	-0.008***
	(0.000)	(0.000)	(0.001)	(0.002)
Maturity	0.001***	0.000**	0.012***	0.001***
	(0.000)	(0.000)	(0.001)	(0.000)
Age	0.000***	0.000	0.003***	0.000
	(0.000)	(0.000)	(0.001)	(0.000)
Married	0.003***	-0.000	0.035***	-0.004
	(0.001)	(0.001)	(0.008)	(0.005)
Education	0.006***	0.002***	0.064***	0.018***
	(0.001)	(0.000)	(0.007)	(0.004)
Income	-0.001***	-0.001***	-0.011***	-0.008***
	(0.000)	(0.000)	(0.003)	(0.002)
Car owner	0.008***	0.001	0.084***	0.008
	(0.002)	(0.002)	(0.018)	(0.017)
Homeowner	-0.011***	-0.002***	-0.127***	-0.021***
	(0.001)	(0.001)	(0.010)	(0.007)
Population	-0.030	-0.004	-0.337	-0.031
	(0.020)	(0.013)	(0.216)	(0.120)
GDP	-0.009***	-0.033***	-0.094***	-0.306***
	(0.003)	(0.009)	(0.036)	(0.077)
Constant	0.244*	0.360***	2.689*	3.261***
	(0.144)	(0.120)	(1.562)	(1.089)
Year-Month Fixed Effects	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes
Observations	287,228	93,466	287,228	93,466
Adjusted R^2	0.020	0.045	0.021	0.045

The table reports the results of estimating $Y_{it} = \alpha_t + \beta_1 Policy + \beta_2 Policy \times Tier1 + \gamma Z_{it} + X_t + \text{FixedEffects} + \varepsilon_{it}$, where *Policy* is the indicator for the implementation of the housing policy, which requires the minimum down payment ratio to be 65% instead of 60% for a second home in 2013. The dependent variable is *Success RE* in Columns (1)—(2), and the dependent variable is the logarithm of the real estate loan funded in Columns (3)—(4). Clustered standard errors are presented in parentheses. *** denotes the significance at 1%, ** denotes the significance at 5%, *denotes the significance at 10%, respectively an example. The state media in Shenzhen estimated that among those properties purchased in December 2015 with mortgages worth more than 1 trillion RMB, one-third were deemed speculative. Considering that home buyers are required to pay 5% more down-payment after the intervention policy, i.e., loan-to-value for the second home purchase decreases from 40 to 35%, the size of funding that online lending can provide is considerably large in economic magnitude in first-tier cities and diverges between first-tier cities and the rest of China (Jiang et al., 2019; Senney, 2018). As a result, new property sales in China's first-tier cities grew 14% in 2015 compared with about 7% nationwide,[7] which could be mainly due to such real estate financing through online lending.

Policy Implication and Conclusion

This paper analyzes whether and how individual risk-taking affects real estate financing through FinTech. Using the loan data from an online platform in China, we document that households employ online loans to meet the increasing down-payment requirement during the housing policy restrictions. Individual investors are likely to fund riskier real estate loans with higher expected returns. Compared with other loans, riskier real estate loans have access to more funding in shadow banking. We also document that real estate loans experience higher ex-post default rates, the impact of which is more pronounced when the credit is the constraint.

Our results have significant policy implications in terms of government interventions, macroprudential policies, financial intermediary issues, and mechanisms of housing market financing. Our results imply that the existence of the shadow banks affects the economic outcome of macroprudential policies, which mainly focus on conventional bank loans. As the existence of online loans attracts a lot of lower-quality borrowers and speculators, the future cash flow for these lower-quality borrowers is uncertain and underestimated. In this regard, a significant correction in the housing market could lead to a high default in the shadow banks and further spread to the traditional banking system. The regional evidence indicates that the real estate loan requests and approval rates tend to be higher in those regions with higher housing prices and down-payment requirements. This is particularly pronounced in China's megacities. Though China's megacities only comprise less than 10% of the overall market, our results underline concerns over the impact of the housing boom through shadow banks on the overall economy. If the speculators use the online loans for the down payment, such mortgage will increase the systemic risk to commercial banks.

[7] Source: Haver Analytics.

The overall results suggest that the housing policy transmission channel in the real estate market may be driven by individual risk-taking, which provides new insights for Chinese regulators to advance their risk management on the household leverage and real estate sector.

Appendix 1

Table 11 Variable Definition

Variable Name	Definitions
Dependent Variables	
Success	A dummy variable that equals one if a loan is granted and zero otherwise
Success RE	A dummy variable that equals one if a real estate loan is granted and zero otherwise
Loan Amount	The loan amount funded (in logarithm)
Loan Amount RE	The real estate loan amount funded (in logarithm)
Default	A dummy variable that equals one if the loan is not entirely repaid and zero otherwise
Independent Variables	
Risk Measures	
Credit Grade	The credit grade ranges from 1–7, in which 1 denotes loan applications with the lowest risk, and 7 denotes loan applications with the highest risk
Loan Characteristics	
Return	The expected return of the loan, which equals promised lender yield minus expected loss. The expected loss is calculated based on the past default rate
Maturity	Loan listing term in months
Borrower Characteristics	
Monthly Income	Borrower's monthly income level in RMB (1–7), in which 1 represents 0–1000,2represents 1000–2000,3 represents 2000–5000,4 represents 5000–10,000,5 represents 10,000–20,000,6 represents 20,000–50,000,7 represents 50,000 and above
Homeowner	A dummy variable that equals one if the borrower is a homeowner and zero otherwise
Car owner	A dummy variable that equals one if the borrower is a car owner and zero otherwise
Education	Borrower's education level: one for high school and below, two for college, three for undergraduate, four for graduate and above
Age	The age of the borrower
Married	A dummy variable, whether the borrower is married or not
Macro Controls	
Population	The population of the city where the borrower residence (in logarithm)
GDP	GDP of the city where the borrower residence (in logarithm)

Appendix 2

Table 12 Determinants of Credit Rating

	Credit Grade
Age	-0.0243***
	(0.0003)
Married	-0.0784***
	(0.0049)
Education	-0.0410***
	(0.0029)
Income	-0.0371***
	(0.0019)
Car owner	0.3777***
	(0.0150)
Homeowner	0.0840***
	(0.0047)
ID_Verify	-0.0875***
	(0.0059)
Education_Verify	0.5238***
	(0.0120)
Income_Verify	-0.1004***
	(0.0059)
Title_Verify	0.6016***
	(0.0230)
Job_Verify	-3.6529***
	(0.0066)
Constant	7.9583***
	(0.0121)
No. of Observations	287,228
R^2	0.7230

This table presents the determinants of borrower risk rating. The dependent variable is *Credit Grade*. The variables of interest are *Age, Married*, *Education, Income, Car owner,* and *Homeowner. ID_Verify, Education_Verify, Income_Verify, Title_Verify,* and *Job_Verify* are verifications for national ID, education degree, income statement, employment letter, and credit record submitted by borrowers. Coefficient estimates are presented with T-statistics in parentheses. ***, **, and * indicate the significance at 1%, 5%, and 10% levels, respectively

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