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Informal borrowing and home purchase: Evidence from urban China[☆]

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ABSTRACT

In this paper, we provide a new explanation for the co-existence of huge housing demand and low dependence on mortgage loans in urban China, focusing on the effect of households' informal borrowing from relatives and friends. Empirical analysis based on a national-level household survey suggests that because of the low financial cost of informal borrowing, households tend to borrow as much as possible from informal channels until they reach the constraint determined by their social capital, which significantly crowds out formal borrowing such as mortgage loans from commercial banks. Additionally, the existence of informal borrowing significantly increases households' housing demand. Understanding these effects is especially important in regions with less mature financial systems.

1. Introduction

The demand for urban housing in China has increased rapidly since the housing reform in the late 1990s (Wang, 2011), and China has become the largest housing market globally. According to the National Bureau of Statistics of China (NBSC), urban households spent 43.4 trillion RMB on housing purchases between 2000 and 2014 and over 7 trillion RMB in 2014 alone. The living space per capita in urban China has increased continuously from about 20 sq. m. in 2000 to over 34 sq. m. in 2014. Housing has also become the largest asset in urban households' balance sheets (Li and Wu, 2014).

This huge housing demand in China has attracted global research interest, and two facts are highlighted in the literature. The first is the large expenditure on housing purchases compared with buyers' current incomes (Yang and Shen, 2008; Yang and Chen, 2014). Wu et al. (2012, 2015) find the average price-to-income ratio in 35 major Chinese cities to be much higher than in most developed economies such as the U.S. Fang et al. (2015) find the average price-to-income ratio to be over 10 in first-tier cities and emphasize that even households in the bottom-income cohort are actively involved in purchasing residential units under huge financial burdens.

As a conventional method of formal borrowing, mortgage loans are widely regarded as an important financing channel in households' housing purchases (Leece, 2008). However, Chinese households are well known for their low dependence on mortgage loans from commercial banks (Deng and Fei, 2008). According to the statistics from the Urban Household Survey conducted by NBSC, only 17% of homebuyers in urban China received mortgage loans between 2002 and 2009. In 2012, the outstanding balance of residential mortgages made up only 14.5% of GDP in China, which was much lower than in Japan (39%), the U.S. (72%), and the U.K. (86%).[1]

These two facts jointly suggest that China's urban households must depend on other channels to finance their home purchases. Whereas most studies connect these facts to the high saving rate in China (Chamon and Prasad, 2010), in this paper, we focus on another informal financial arrangement: borrowing from relatives and friends based on social capital. Our empirical results, based on the Chinese Household Finance Survey (CHFS), indicate that such informal borrowing in China plays an important role in households' home purchases. Two findings are particularly noteworthy. First, because of the lower cost of informal borrowing, households tend to borrow from informal channels as much as possible until they reach the constraint given by their social capital; thus, informal borrowing crowds out formal borrowing such as mortgage loans from commercial banks. Second, informal borrowing can significantly boost home purchasers' housing demand; in other words, households who have better social capital and thus access to more informal borrowing tend to spend significantly more on home purchases and to buy larger and better

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housing units, controlling for other factors. The above findings are amplified in regions with less developed financial systems. We believe that these findings provide a new key insight into the underlying logic behind the booming housing demand in urban China during the previous decade.

In addition to offering better insight into Chinese urban housing markets, this paper contributes to the growing body of literature on the informal financial system. The informal financial system is suggested to play an important role in developing countries, although most research has concentrated on its effects on the corporate sector (Allen et al., 2005; Ayyagari et al., 2010) or rural households (Jia et al., 2010; Turvey et al., 2010; Khoi et al., 2013). To the best of our knowledge, this paper provides the first evidence of the importance of informal borrowing in urban households' home purchase behaviors, further highlighting the need to investigate informal financial channels for a better understanding of the financial system in developing countries such as China.

The remainder of this paper proceeds as follows. The next section develops the core hypothesis regarding the role of informal borrowing on mortgage and housing demand. Section 3 describes the survey data and the empirical strategy. Section 4 discusses the empirical findings. Section 5 concludes the paper.

2. Hypothesis of the analysis

A key feature of informal borrowing in developing countries, as suggested by existing literature, is that its explicit (monetary) financing costs are typically lower than those of formal borrowing (e.g., through bank loans). These lower costs result from three features of informal borrowing: information transparency, social guarantee, and potential reciprocity.

First, information asymmetry problems can be substantially alleviated in informal borrowing systems. As highlighted by Stiglitz and Weiss (1981) and many subsequent papers, information asymmetry is a major challenge for lenders in formal credit markets. This problem is especially important in emerging mortgage markets of developing countries because the borrowers are typically informationally opaque. In contrast, in informal borrowing, information is more likely to be symmetrical and transparent due to the mutual understanding based on social networks between family members and friends (Besley and Coate, 1991). This information transparency can help identify and lock out high-risk borrowers, eliminating the adverse selection problem and reducing transaction costs (Turvey and Kong, 2010; Ghatak, 1999).

Second, in informal borrowing systems, borrowers implicitly pledge their social capital as collateral, which mitigates the potential moral hazard problem and reduces default risk (Salas and Saurina, 2002). In most cases, borrowers do not need to pledge their housing units as collateral in informal borrowing. However, at delinquency or default, they are exposed to high social costs, including the loss of future benefits (such as informal loan access), social stigma, or even expulsion from the social network (Guiso et al., 2009). Such social pressure can effective in reducing default in informal borrowing systems and thus also contributes to lower financial costs.

Finally, lenders in informal borrowing systems are willing to accept lower monetary interest rates because they expect additional returns from other sources. In mortgage markets, interest collected from borrowers serves as the major or even only source of profit for lenders. However, in the spirit of mutual aid, socially embedded ties in informal borrowing facilitate coordination and cooperation for mutual-benefit norms (Lin, 1999), which provides broader potential reciprocity in the long term for lenders. Lenders can reasonably expect to receive some other monetary or non-monetary returns from borrowers, such as emergency medical aid, valuable information sharing, or emotional support (Nahapiet and Ghoshal, 1998; Franzen and Hangartner, 2006). Controlling for the overall expected return, the existence of potential reciprocity enables lenders to lower monetary interest rates.

The above three factors suggest that the financial cost of informal borrowing may be much lower than the cost of formal bank loans, even as low as a (monetary) interest rate of zero (Karaivanov and Kessler, 2013). In housing markets, the use of such lower-cost informal borrowing will affect households' purchase and financing behaviors in at least two ways. First, due to more favorable interest rates of informal channels, a household would prefer to choose informal borrowing to finance its home purchase, if feasible, given its budget constraint. This would lead to a reduction in demand for formal credit, generating our first hypothesis:

Hypothesis 1. Because of lower financial costs, informal borrowing will crowd out mortgages from commercial banks to finance households' home purchases.

Second, the existence of lower-cost informal borrowing will increase the demand for housing. Capital cost is a major component of user cost in housing markets (Poterba, 1984), and the lower real user cost resulting from the lower capital cost will have a positive effect on housing demand. This generates our second hypothesis:

Hypothesis 2. Informal borrowing will increase households' housing demand.

One noteworthy factor is the implicit cost of informal borrowing (Madestam, 2014). Because most informal borrowing from family and friends is done in the form of an unwritten/non-contractual commitment with leniency and flexibility, borrowers are subject to higher pre-payment requirements due to the financial urges of the lender (Fafchamps and Lund, 2003). Borrowers also face a high delinquency cost as mentioned above (Lee and Persson, 2016; Karaivanov and Kessler, 2013). Moreover, the establishment and maintenance of social networks requires some costs, including actual expenditures (such as excess costs of dining-out and travel costs), opportunity cost (such as time), and pressure from certain ethnic norms (Glaeser et al., 2002). However, the literature suggests that all these implicit costs are typically underestimated or even ignored by borrowers in developing countries (Boucher and Guirkinger, 2007), including China (Chen and Chen, 2009; Chen and Chen, 2004). Thus, we believe that the existence of implicit costs do not significantly alter the effects of informal borrowing on mortgage and housing demand. We provide some preliminary evidence of this at the end of the empirical analysis.

3. Data and empirical design

3.1. Data description and variable identification

Our empirical analysis is based on data from the 2013 China Household Finance Survey (CHFS). The CHFS is a nationwide micro-level survey conducted by the Survey and Research Center for China Household Finance, Southwestern University of Finance and Economics (SWUFE). Using a stratified three-stage probability proportional to size (PPS) random sample design,[2] the 2013 survey includes 18,000 urban households from 262 districts/counties in 29 provinces. More details on the survey are available in Gan et al. (2013).

We obtain our sample from the following two steps. First, we exclude all rental households, which account for about 10.5% of the urban sample in the data. Second, we drop all observations with null or abnormal values in the key variables (such as households with negative income,

[2] The primary sampling units (PSU) include 2585 counties (including county level cities and districts) from 31 provinces (including provincial cities) in China. The second stage of sampling involves selecting residential committees/villages from the counties/cities selected in the first stage. The last stage is to select households from the residential committees/villages chosen in the second stage. Every stage of sampling is carried out using the PPS method and is weighted by population size.

housing areas exceeding 500 m^2, and unit housing values exceeding 100 million RMB). The final sample includes 8491 observations.[3]

Detailed information on the home purchase behavior for the current dwelling unit is available, including housing value, unit size, funding sources at the time of purchase, and the year when the transaction occurred. We are able to obtain information on both informal and formal loans for housing purchases. The majority of households relied on informal borrowing as their main external financing channel. In the sample, only 14% of respondents obtained mortgage loans from commercial banks at the time of home purchase. The average loan value was 21,000 RMB, and the average loan-to-value ratio (LTV) was only 35%, which is far below the average ceiling level of 70% in China. In contrast, over 32% of home buyers borrowed informally from their relatives or friends, of whom 14% also took out mortgages and 86% fully depended on the informal borrowing. The average amount of the informal borrowing was 70,300 RMB—higher than the average formal loan value—and the average LTV was 45.4%. The average reported interest rate for informal borrowing was only 0.43%, much lower than the average reported interest rate for mortgage loans (6.05%).

Households' access to informal borrowing is largely determined by their social capital (Turvey et al., 2010). Although it is very difficult to directly and quantitatively measure a household's social capital, we follow the Weak Ties Theory (Granovetter, 1985) and adopt the following three proxies.[4]

Firstly, and perhaps most intuitively, a household will have more social connections and a higher possibility of obtaining social capital if its members have more relatives living in the same city (Stokes, 1983). Therefore, we choose the number of relatives living in the same city (*hnum*) as a proxy to reflect the potential size of the households' social network.

Secondly, it is reasonable to expect that local households will have a larger network of local social connections (Burt, 1992; Knight and Yueh, 2008). Since information of the number of years that the respondents have been living in their current city is not available in the survey, we choose to use a dummy for whether the household has local household registration (i.e., a local *hukou*) as the proxy (*local*). Households with a local *hukou* are likely to have lived in their current city for a longer period and thus to have a larger local social network. In addition, according to the theory of identity-based exclusion, households with a local *hukou* will find it less difficult to establish and maintain social networks with local urban residents (Zhan, 2011), which also helps them accumulate social capital.

Besides the above two proxies for the size of respondents' social networks, we also introduce a proxy for the respondent's status, or relative importance, in his/her social network. Individuals located in the centers of the network are in advantageous positions with more and stronger connections, and they can obtain more support than individuals located at the margins of the social network can (Lin, 1999; Scott, 2012). Following Brown et al. (2011), we choose net cash gifts from the social network (*social*) as the proxy for social network status, which is defined as the net amount of cash gifts the household received from events such as festivals, weddings, funerals, and birthdays during the previous year. We assume that households who have larger net social incomes will have higher positions in the social network and thus have better access to informal borrowing.

Several other household attributes are introduced as control variables, including household disposable income (including salary, subsidies, income from financial assets, and transfer income), household savings, the age of the household head, the gender of the household head, the marriage status of the household head, the risk attitude of the household head, and the share of young and elderly members in the household. We also control for local housing market information, including the average housing unit price (*price*) and the average housing unit size (*area*) at the community level. Finally, we include time[5] and regional fixed effects. The summary description of the variables is listed in Table 1.

Table 2 compares the attributes of households with and without informal borrowing at home purchase. Compared with those without any informal borrowing, households with informal borrowing have more relatives living in the same city, a higher probability of having a local *hukou*, and larger net incomes from their social networks. These results provide some preliminary evidence on the validity of our social capital proxies.

3.2. Empirical Strategies

The empirical analysis involves two major steps. In the first step, we test the effect of informal borrowing on mortgage borrowing from commercial banks, including both the probability of using a mortgage and the loan-to-value ratio. In the second step, we investigate the effect of informal borrowing on housing demand.

For the first step, we write the general recursive system as

$$lninformal^* = \alpha_1 + \beta_1 social\ \ network\ \ variables_i + \beta_2 control_i + \varepsilon_i$$
$$lninformal = \begin{cases} lninformal^* & if \quad lninformal^* > 0 \\ 0 & otherwise \end{cases} \tag{1}$$

$$D\_mortgage^* = \alpha_2 + \beta_3 lninformal^* + \beta_4 control_i + \partial_i$$
$$D\_mortgage = \begin{cases} 1 & if \quad D\_mortgage^* > 0 \\ 0 & otherwise \end{cases} \tag{2}$$

$$LTV^* = \alpha_3 + \beta_5 lninformal^* + \beta_6 control_i + \gamma_i$$
$$LTV = \begin{cases} LTV^* & if \quad LTV^* \geq \overline{LTV} \\ 0 & otherwise \end{cases} \tag{3}$$

where *lninformal* denotes the amount of informal borrowing, which is left censored at 0, *D_mortgage* is a dummy variable denoting whether the household uses mortgage loans from commercial banks, and *LTV* denotes the loan-to-value ratio of mortgage loans, which is right censored at $\overline{LTV}$.[6] The latent variables $lninformal^*$, $D\_mortgage^*$, and LTV^* are not fully observed. The vector $control_i$ refers to the set of control variables, including basic household characteristics and year and provincial fixed effects.

There are two major challenges in estimating the above empirical model. First, due to the censoring problem, we do not fully observe informal and formal borrowing (i.e., the latent variables $lninformal^*$, $D\_mortgage^*$, and LTV^*). Second, informal and mortgage borrowing

[3] We lost about half of the observations here because those respondents did not provide information on mortgage use at home purchase. The following two pieces of evidence suggest that our data cleaning process does not lead to sampling bias. First, we apply *t* tests to compare the key variables between the original data and our restricted sample, and no significant differences are found. Second, the results are robust to using the Heckman two-stage model to control for the potential sampling bias. Both results are available upon request.

[4] The literature also suggests some other indicators on social networks or social capital, but they are not adopted here. For example, some studies adopt population density to reflect social network density, and suggest that the social connections should be weaker in areas (e.g., larger cities) with higher population density (Fischer, 1982). Some research also argues that the network density is stronger in South China, compared with North China, due to the traditional clan power resulting from historical reasons (Tang, 2017). We do not include these two proxies because we focus on household-level, rather than region-level, variations. In addition, some literature emphasizes that the social network needs to be maintained by social activities such as parties and dining, and so uses dining-out expenditures as a proxy for social network density (Uzzi, 1999). We do not include this variable because of its potential endogeneity – households might have to pay more on dining-out expenditures after they borrow from relatives/friends. However, our empirical results remain robust if we include the above three proxies, and the results are available upon request.

[5] We use year fixed effects to control for when the respondents purchased their current dwelling units.

[6] In our empirical analysis, we take $\overline{LTV}$ = 0.7 as an average measure based on the mortgage policy in China.

Table 1
Statistical description of selected variables.

Variable	Definitions	Obs.	Mean	Std. Dev.
Informal and formal borrowing				
D_informal	whether the household borrowed from relatives/friends when buying the current residential unit; 1 = yes, 0 = o/w	8491	0.325	0.468
D_mortgage	whether the household received a mortgage loan from a commercial bank when buying the current residential unit; 1 = yes, 0 = o/w	8491	0.143	0.350
informal	total amount of informal borrowing; in 10,000 RMB	8491	16.095	50.880
mortgage	total amount of mortgage loan; in 10,000 RMB	8491	43.500	170.447
LTV	mortgage loan-to-housing value ratio	8491	0.046	0.148
Social network information				
hnum	number of relatives living in the same city	8491	2.593	1.501
local	whether the household head has a local *hukou*; 1 = yes, 0 = o/w	8491	0.491	0.500
social	the logarithm of annual social network income (in 10,000 RMB) minus the logarithm of annual social network expenditures	8491	−3.762	4.305
Household basic information				
income	household annual disposable income including salary, subsidies, income from financial assets, and unregular income; in 10,000 RMB	8491	10.587	1.326
saving	household savings; in 10,000 RMB	8491	38.242	146.067
headage	age of the household head	8491	49.077	13.179
male	gender of the household head; 1 = male, 0 = female	8491	0.771	0.420
married	marriage status of the household head; 1 = married, 0 = o/w	8491	0.905	0.294
D_risker	whether the household head is a risk lover; 1 = yes, 0 = o/w	8491	0.325	0.468
share_young	the share of young members (18 years old and below) in the household	8491	0.031	0.091
share_old	the share of old members (60 years old and above) in the household	8491	0.170	0.301
Macro market information				
price	average housing price in the community; in 10,000 RMB per square meter	8491	2.716	1.150
area	average housing unit size in the community; in square meters	8491	54.244	4.130

Notes:
1. The dummy variable *D_risker* is extracted from a hypothetical question in the survey: if the interviewee chooses the lottery of 10,000 with a 50% winning rate rather than the lottery of 5000 with a 100% winning rate, we define him as a risk lover.
2. In the empirical analysis, *ln* denotes the logarithm of the variable.

Table 2
t-statistic of the difference between non-informal and informal borrowers.

Variables	Households without informal borrowing			Households with informal borrowing			Mean difference
	Observation	Mean	Std. Dev.	Observation	Mean	Std. Dev.	
hnum	5733	2.439	1.422	2758	2.913	1.550	−0.474***
local	5733	0.460	0.497	2758	0.554	0.480	−0.094***
social	5733	−3.892	4.373	2758	−3.491	4.146	−0.401***

Notes:
** $p < 0.05$,
*$p < 0.1$.
*** $p < 0.01$.

could be jointly decided by households' latent characteristics that cannot be directly controlled for. The dependent variables (informal and formal borrowing) might be generated with correlated errors (ε_i and ∂_i, ε_i and γ_i), causing omitted variable bias. To overcome these two potential problems, we use the conditional-recursive mixed process (CMP) in our empirical analysis. The CMP estimates multi-equation, mixed process models, potentially with hierarchical random effects. It broadens the classical seemingly unrelated regressions (SUR) model by allowing for non-continuous dependent variables in individual equations (such as the censored variables *lninformal* and *LTV* and the binary variable *D_mortgage*). By using the maximum likelihood approach to estimate equations as a system, the CMP estimator has potential efficiency gains compared with a two-step estimator. To provide a reliable estimate of the effect of the social network on mortgage demand, the matrix form of the CMP estimation of (1) and (2) can be rewritten as

$$\begin{aligned} \boldsymbol{y}^{*\prime}\boldsymbol{\Gamma} &= \boldsymbol{y}'\boldsymbol{\Delta} + \boldsymbol{x}'\mathbf{B} + \boldsymbol{\epsilon} \\ \mathbb{E}(\boldsymbol{\epsilon x}) &= \mathbf{0} \\ \boldsymbol{\epsilon} &\sim \mathcal{N}(0, \Sigma) \end{aligned} \tag{4}$$

where $\boldsymbol{\Gamma}$ is an upper triangular matrix with 1 along the diagonal,

$\boldsymbol{y}^{*\prime} = (lninformal^{*}, D\_mortgage^{*})$,
$\boldsymbol{y}' = (lninformal, D\_mortgage)$, and
$\boldsymbol{x}' = (social network variables, control)$.

Solving for $\boldsymbol{y}^{*}$ in the first equation, we have

$$\begin{aligned} &\boldsymbol{y}^{*\prime} = \boldsymbol{y}'\boldsymbol{\Delta}\boldsymbol{\Gamma}^{-1} + \boldsymbol{x}'\mathbf{B}\boldsymbol{\Gamma}^{-1} + \boldsymbol{\epsilon}\boldsymbol{\Gamma}^{-1} = \boldsymbol{y}'\mathbf{\Pi} + \boldsymbol{x}'\mathcal{B} + \mathcal{R} \\ &\mathcal{R} \sim \mathcal{N}(0, \Omega) \qquad \Omega = \boldsymbol{\Gamma}^{-1\prime}\Sigma\boldsymbol{\Gamma}^{-1} \end{aligned} \tag{5}$$

where $\mathbf{\Pi}$ is strictly upper triangular.

The multiplication by $\boldsymbol{\Gamma}$ is a transformation with a Jacobian that has a determinant of 1 ($|\boldsymbol{\Gamma}| = 1$). Thus, the estimating equation of $\boldsymbol{y}^{*\prime}$ has the form of a fully observed recursive system and can be estimated consistently with maximum likelihood SUR. The maximum likelihood is the integral

$$L_i(\mathbf{B},\Sigma,\boldsymbol{\Delta}; y_i x_i) = \int_{-\infty}^{-\boldsymbol{B}_1 \boldsymbol{x}_{1i}} f_{\epsilon_1}(\epsilon_1) \int_{-\infty}^{-\boldsymbol{B}_2 \boldsymbol{x}_{2i} - \Delta_{12}(\boldsymbol{B}_1 \boldsymbol{x}_{1i} + \epsilon_1)} f_{\epsilon_2|\epsilon_1}(\epsilon_2) d\epsilon_2 d\epsilon_1 \tag{6}$$

where $f_z(\bullet)$ is the probability distribution function for z.

Table 3
Informal borrowing and the probability of adopting a mortgage.

	(1)	(2)	(3)	(4)
First stage of lninformal				
hnum	0.0262***			0.0231***
	(0.0111)			(0.0113)
local		0.0640***		0.0495***
		(0.0394)		(0.0407)
social			0.0024***	0.00210**
			(0.00364)	(0.00368)
Control variables	Yes	Yes	Yes	Yes
D_mortgage				
lninformal	−0.0164***	−0.0188***	−0.0177***	−0.0085*
	(0.0246)	(0.0199)	(0.0265)	(0.0223)
lnincome	0.0135***	0.0100**	0.0108**	0.0131***
	(0.0193)	(0.0197)	(0.0222)	(0.0190)
lnsaving	−0.0041***	−0.0044***	−0.0042***	−0.0042***
	(0.00408)	(0.00383)	(0.00397)	(0.00404)
headage	−0.0074***	−0.0060**	−0.0061**	−0.0072***
	(0.010001)	(0.0102)	(0.0110)	(0.00994)
headage2	0.0000396*	0.0000221	0.0000225	0.0000374*
	(0.000106)	(0.000105)	(0.000113)	(0.000105)
male	−0.0099	−0.0047	−0.0040	−0.0095
	(0.0449)	(0.0435)	(0.0458)	(0.0444)
married	0.0509***	0.0598***	0.0593***	0.0523***
	(0.0711)	(0.0666)	(0.0672)	(0.0706)
D_risker	0.0163**	0.0166**	0.0167**	0.0162**
	(0.0379)	(0.0348)	(0.0354)	(0.0376)
share_young	−0.0126	−0.0134	−0.0126	−0.0129
	(0.197)	(0.179)	(0.181)	(0.195)
share_old	−0.0724***	−0.0740***	−0.0725***	−0.0730***
	(0.0984)	(0.0941)	(0.0936)	(0.095)
lnprice	0.0401***	0.0431***	0.0423***	0.0396***
	(0.0237)	(0.0245)	(0.0244)	(0.0241)
lnarea	0.0274***	0.0309***	0.0278***	0.0287***
	(0.05004)	(0.0456)	(0.0464)	(0.096)
Education and Occupation	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	8491	8491	8491	8491
LR chi2	1427.2***	1374.5***	1330.7***	1461.3***
Log likelihood	−7337.019	−7363.369	−7385.256	−7319.968

Notes:
This table reports marginal effects. Standard deviations are in brackets.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

We can apply the CMP to estimate (1) and (3) to investigate the effect of the social network on the amount of mortgage loan borrowing.

In the second step, we apply the Propensity Score Matching (PSM) method to match each household with informal borrowing (treatment group) to the most similar household without informal borrowing (counterfactual group). Then, we consider the housing demand (housing area and unit price) of the matched counterfactual group as the "basic housing demand" and take the difference in housing demand between the treatment group and the counterfactual group (namely, *D_area* and *D_unit price*) as dependent variables to investigate whether more informal borrowing leads to higher housing demand. That is,

$$D\_area = \alpha_4 + \beta_7 lninformal_i + \beta_8 lnmortgage_i + \beta_9 control_i + \theta_i \quad (7)$$

$$D\_unit\ price = \alpha_5 + \beta_{10} lninformal_i + \beta_{11} lnmortgage_i + \beta_{12} control_i + \vartheta_i \quad (8)$$

4. Empirical results

4.1. Informal borrowing and mortgage use

We first focus on the effect of informal borrowing on the probability of adopting mortgage loans. The results based on the CMP process are shown in Table 3.

The first part of the results focuses on the effect of social capital on the amount of informal borrowing. The coefficients on *hnum, local*, and *social* are all positive and statistically significant, which is consistent with our expectation. A household with a larger social network (*hnum* and *local*) or that locates centrally in its social network structure (*social*) will have better access to social capital and thus can borrow more from informal channels.

The second part of the regression shows the significantly negative effect of informal borrowing on the probability of adopting a mortgage (*D_mortgage*), which supports our first hypothesis. Controlling for other factors, if the amount of informal borrowing increases by 1%, the probability of taking out a mortgage declines by 0.85 percentage points. Because of its relatively low cost, borrowing informally from relatives and friends crowds out mortgages.

Next, we turn to the effect of informal borrowing on the mortgage amount borrowed, as shown in Table 4. Again, the regression implies a significant negative relationship between informal borrowing and mortgage demand (*LTV*). When the amount of informal borrowing increases by 1%, the loan-to-value ratio decreases by 1.3 percentage points. This is also consistent with our first hypothesis: informal borrowing not only lower the probability of obtaining a mortgage, but also decreases total mortgage demand. The results in Tables 3 and 4 provide a potential reason for the low mortgage participation rate in urban China.

Table 4
Informal borrowing and the LTV of mortgages.

	(1)	(2)	(3)	(4)
First stage of lninformal				
hnum	0.0262***			0.0227***
	(0.0111)			(0.0114)
local		0.0647***		0.0509***
		(0.0388)		(0.0403)
social			0.0025***	0.0022**
			(0.00354)	(0.00364)
Control variables	Yes	Yes	Yes	Yes
LTV				
lninformal	−0.0118**	−0.0230***	−0.0219***	−0.0127**
	(0.0241)	(0.0166)	(0.0224)	(0.0209)
lnincome	0.0149***	0.0111**	0.0110**	0.0145***
	(0.0192)	(0.0191)	(0.0216)	(0.0189)
lnsaving	−0.0047***	−0.0047***	−0.0046***	−0.0046***
	(0.00398)	(0.00368)	(0.00385)	(0.00390)
headage	−0.0069***	−0.0054**	−0.0055**	−0.0068***
	(0.00984)	(0.0097)	(0.0105)	(0.00974)
headage2	0.0000342	0.0000157	0.0000156	0.0000329
	(0.000104)	(0.000110)	(0.000107)	(0.000102)
male	−0.0134	−0.0076	−0.0067	−0.0127
	(0.0441)	(0.0421)	(0.0444)	(0.0434)
married	0.0498***	0.0573***	0.0571***	0.0505***
	(0.0688)	(0.0636)	(0.0641)	(0.0676)
D_risker	0.0196**	0.0197**	0.0198**	0.0195**
	(0.0369)	(0.033)	(0.0337)	(0.0361)
share_young	−0.0251	−0.0260	−0.0249	−0.0259
	(0.193)	(0.169)	(0.172)	(0.188)
share_old	−0.0803***	−0.0795***	−0.0777***	−0.0801***
	(0.0951)	(0.0860)	(0.0889)	(0.0931)
lnprice	0.0396***	0.0401***	0.0430***	0.040***
	(0.0234)	(0.0235)	(0.0237)	(0.027)
lnarea	0.0105**	0.0230**	0.0192*	0.0210**
	(0.0489)	(0.0430)	(0.0436)	(0.049)
Education and occupation	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	8491	8491	8491	8491
LR chi2	166.88***	1557.00***	1511.37***	1463.23***
Log likelihood	−7456.476	−7500.611	−7523.425	−7457.495

Notes:
This table reports marginal effects. Standard deviations are in brackets.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

4.2. Informal borrowing and housing demand

In this section, we investigate further the effect of informal borrowing on housing demand using the matched sample. The results are shown in Table 5. The coefficients of informal borrowing are significantly positive in both the unit size and unit price specifications, which provides direct support for our second hypothesis. Households with better access to informal borrowing convert their social capital into demand for larger housing quantity and better housing quality. Specifically, when the informal borrowing acquired by a household increases by 1%, the floor area of the dwelling unit purchased increases by around one square meter; additionally, the average unit price increases by about 2000 RMB per square meter. We believe that such results at least partly explain the huge housing demand in urban China.

In the latter two columns of Table 5, we introduce the amount of commercial bank mortgage borrowing to the model. While the coefficient on informal borrowing remains nearly unchanged, we find that the coefficient on mortgage borrowing is significantly negative in the unit size and unit price models. One possible explanation is that when a household must rely more on mortgage loans, the repayment burden reduces the household's housing demand.

4.3. Robustness tests

The empirical results above are consistent with a series of robustness tests.

4.3.1. Potential reverse causality

A key concern with our empirical results is reverse causality: although our hypotheses argue that the existence of informal channels leads to both lower reliance on mortgage loans and higher housing demand, another possible explanation is that households must seek informal borrowing if they plan to purchase more expensive dwelling units but fail to get sufficient mortgage loans from commercial banks. We rule out this possibility using three tests. The results are shown in Table 6.

First, we directly use information on respondents' mortgage application records in the survey. As mentioned earlier, in our sample, only 14.3% of respondents obtained mortgage loans from commercial banks. 79.9% of respondents answered that they did not need (and thus did not apply for) mortgages from commercial banks at home purchase, and only 3.2% of respondents reported that the application for mortgage loans were rejected by commercial banks due to low

Table 5
Informal borrowing and housing demand.

	(1) *D_area*	(2) *D_unit_price*	(3) *D_area*	(4) *D_unit price*
lninformal	0.996**	1.911***	0.952**	1.878***
	(0.461)	(0.350)	(0.461)	(0.349)
lnmortgage			−1.718**	−1.409**
			(0.586)	(0.444)
lnincome	5.461***	1.763	5.842**	2.125
	(2.062)	(1.562)	(2.037)	(1.544)
lnsaving	1.148**	0.909**	1.074**	0.857**
	(0.539)	(0.408)	(0.537)	(0.407)
headage	0.682	−0.297	0.354	−0.570
	(1.316)	(0.997)	(1.318)	(0.998)
headage2	−0.00348	0.00430	−0.000720	0.00659
	(0.0134)	(0.0101)	(0.0134)	(0.0101)
male	−2.628	−0.854	−2.841	−1.098
	(6.208)	(4.704)	(6.195)	(4.694)
married	2.919	−11.25	3.473	−10.85
	(9.360)	(7.093)	(9.345)	(7.081)
D_risker	4.803	1.346	5.253	1.694
	(4.987)	(3.779)	(4.981)	(3.774)
share_young	26.95	−11.17	26.05	−12.28
	(1.16)	(−0.64)	(23.13)	(17.53)
share_old	8.707	−8.307	7.251	−9.378
	(0.73)	(−0.92)	(11.97)	(9.068)
lnprice	2.963	−2.117	4.019	−1.239
	(3.025)	(2.292)	(3.029)	(2.295)
lnarea	108.7***	−17.31***	109.2***	−17.02***
	(6.085)	(4.611)	(6.008)	(4.552)
Education and occupation	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	2758	2758	2758	2758
R-sq	0.145	0.130	0.148	0.133

Notes:
Standard deviations are in brackets.
* $p < 0.1$.
*** $p < 0.01$.
** $p < 0.05$.

income, poor credit records, or collateral deficiency. In the first panel (credit rationing) of Table 6, we exclude households that reported that they failed to obtain formal borrowing from commercial banks. The sample size is reduced to 8374. To control for the potential sample selection bias, we include the calculated inverse Mills ratio of being declined ($lambda\_decline_i$) in the regression. The coefficients on $lninformal_i$ are significant and robust in all regressions.[7]

The second test focuses on the Chinese monetary authority's requirement for mortgage down payments. In most cases, a homebuyer must pay at least 30% as a down payment to obtain a formal loan. If the share of equity payment (i.e., excluding both formal and informal borrowings) reached at least 30% at a household's home purchase, it is reasonable to expect that he/she does not have to depend on informal channels to satisfy the minimum down payment restriction, and is less likely to be bounded by his/her access to formal mortgage loans from commercial banks. Thus, we only include observations with equity payment no less than 30%, and introduce $lambda\_mort_i$, the inverse Mills ratio indicating whether the respondent was bounded by the down payment limit. As shown in the second panel (down payment restriction) of Table 6, the coefficients on informal borrowing are still robust.

Finally, we consider the potential sensitivity of the results to changes in macro-prudential policy in China. To promote economic growth and maintain currency stability, the People's Bank of China has issued a series of policy measures to regulate loan supply since 1995. In the third panel (policy change) of Table 6, we use the dummy variable *D_tighten* to identify years of "mortgage tightening policies," including 2005, 2006, 2007, 2010, and 2011 (Fan and Yavas, 2017). The crowding out effect of informal borrowing on mortgage access is slightly weaker in years with tightened policy, but the effect is always significant. On the other hand, the effect of informal borrowing on housing demand remains nearly unchanged.

4.3.2. Alternative social network proxies

Besides the current proxies for respondents' social capital, we also introduce alternative measures of social capital as a robustness check.

First, considering the potential estimation bias due to multicollinearity among the three social capital proxies, we follow the strategy of Scott (2012) and Ellison et al. (2007) and apply the conventional factor analysis to these three variables. A compound factor index of social capital (*socialnetwork*) is constructed based on the factor loading matrix.[8] As shown in the first two columns of Table 7, when we use this index to replace the three proxies, all results remain robust.

Second, although the current three proxies mainly focus on respondents' "access" to the potential informal lenders, another important factor is the "lending ability" of these potential lenders; in

[7] We also test whether the social capital indicators affect the probability of being declined for a mortgage and find no significant effects.

[8] The eigenvalue of the first factor exceeds 1, and after the Varimax rotation, the cumulative variance contribution of the first factor reaches 75%. Thus, we choose the first factor as the latent (common) factor of our study. The loading matrix after the rotation indicates the correlation between the selected common factor and each observed proxy for social capital. We then use the calculated common factor as the alternative measure of social capital.

Table 6
Effect of informal borrowing: robustness checks for potential endogeneity.

	(1) *D_mortgage*	(2) *LTV*	(3) *D_area*	(4) *D_unit price*
A. Credit rationing				
lninformal	−0.0084**	−0.0126**	1.010**	1.983**
	(0.0240)	(0.0227)	(0.468)	(0.231)
lnmortgage			−1.639**	−1.842**
			(0.590)	(0.291)
lambda_decline	0.9101**	1.0223**	−2.601	−81.21
	(1.809)	(1.751)	(197.9)	(97.40)
Control variables	Yes	Yes	Yes	Yes
N	8374	8374	2673	2673
B. Down payment restriction				
lninformal	−0.0084***	−0.0101***	1.512***	2.676***
	(0.0334)	(0.0368)	(0.504)	(0.346)
lnmortgage			−1.022**	−1.361***
			(0.456)	(0.397)
lambda_mort	−0.3258	−0.4256	−68.36	49.16
	(1.556)	(1.549)	(53.40)	(45.56)
Control variables	Yes	Yes	Yes	Yes
N	7727	7727	2302	2302
C. Policy change				
lninformal	−0.0324***	−0.0147***	0.959**	2.022***
	(0.0084)	(0.0113)	(0.470)	(0.231)
lninformal × D_tighen	0.0036**	0.0007	0.135	−0.502
	(0.0115)	(0.0096)	(1.027)	(0.904)
lnmortgage			−1.760***	−1.439***
			(0.634)	(0.311)
Control variables	Yes	Yes	Yes	Yes
N	8491	8491	2758	2758

Note:
lambda_decline denotes the inverse Mills ratio of “being declined”; *lambda_mort* denotes the inverse Mills ratio of the minimum down payment limit.
Control variables include basic household information such as income, age, age squared, gender, educational background and occupation, marriage status of the household head, share of young and elderly members of all household members, and time and regional fixed effects.
Columns (1) and (2) report marginal effects; columns (3) and (4) report OLS coefficients. Standard deviations are in brackets.
** $p < 0.05$.
*** $p < 0.01$.

other words, the supply of informal borrowing is constrained by amount of liquid assets that friends or relatives can lend. Unfortunately, CHFS cannot provide any direct information on the wealth or income conditions of respondents' friends/relatives. As an indirect measure, we adopt the provincial average per-capita disposable income as a proxy for lending ability (*paveinc*) and include its interaction term with *socialnetwork* in the latter two columns of Table 7. As expected, the interaction term is significantly positive in the model, which suggests that urban households are more likely to convert their social capital into informal borrowing if their relatives and friends are richer. Meanwhile, we find the effect of informal borrowing on mortgage use remain robust. We do not include *paveinc* in the basic specification because it is an indirect measure at the regional level.

4.4. Further discussions

4.4.1. Financial development

The crowding out of formal financing by informal borrowing requires an immature financial market and limited financial channels (Li and Yi, 2007). In light of this, we investigate the sensitivity of our estimates to regional heterogeneity in financial development. Here, provincial financial development status is measured as the average level of provincial long-term debt-to-GDP ratio (*D_avedtgdp*).[9] If a province's ratio is higher than the median value of the entire sample, it is grouped among the more developed areas; otherwise, it is grouped among the less developed areas. We also use the number of banks per 10,000 persons (*pbank*) and the number of automatic teller machines per 10,000 persons (*patm*) as proxies. As shown in Table 8, the coefficients on the interaction terms are all positive and significant, indicating that the effects of informal borrowing on mortgage use and housing demand are both stronger for households in cities with less mature financial systems. This is consistent with the literature, implying that informal borrowing plays a more important role in markets with underdeveloped financial systems with limited financial accessibility.

4.4.2. Risk attitudes and financial literacy

Households with different risk attitudes and financial literacy levels may exhibit different borrowing behaviors. Intuitively, households with higher risk aversion and more sophisticated financial knowledge/experience will be more sensitive to the implicit risk and compounding cost of informal borrowing and thus will borrow less from informal channels.

To test this, we first build an interaction term using the informal borrowing amount and a dummy variable for risk lovers (*D_risker*). We suppose that the risk of informal borrowing is less important for risk lovers than for the risk averse group. In addition, we build a literacy index[10] (*literacy*) to test whether households in urban China are aware of the cost of social capital. Households with more sophisticated knowledge and skills (i.e., with higher financial literacy) may be better able to evaluate borrowing options and manage their finances effectively (Lusardi and Mitchell, 2007).

[9] Data source: MacroChina Database, 2003–2013.

[10] CHFS contains three questions concerning interest rate, inflation rate, and risk diversification. We use factor analysis to build a compound factor index of financial literacy (literacy).

Table 7
Effect of informal borrowing: robustness checks with alternative proxies.

	(1) *D_mortgage*	(2) *LTV*	(3) *D_mortgage*	(4) *LTV*
First stage of lninformal				
socialnetwork	0.0825***	0.0824***	−0.0141	−0.0120
	(0.0301)	(0.0301)	(0.112)	(0.112)
socialnetwork × paveinc			0.0377***	0.0369***
			(0.0423)	(0.0423)
Control variables	Yes	Yes	Yes	Yes
D_mortgage or LTV				
lninformal	−0.0087*	−0.0132**	−0.0071*	−0.0115**
	(0.0223)	(0.0206)	(0.0222)	(0.0210)
Control variables	Yes	Yes	Yes	Yes
N	8491	8491	8491	8491
LR chi2	1466.46***	1648.89***	1481.85***	1663.75***
Log likelihood	−7317.374	−7454.662	−7309.679	−7447.236

Note:
Control variables include basic household information such as income, age, age squared, gender, educational background and occupation, marriage status of the household head, share of young and elderly members of all household members, and time and regional fixed effects.
This table reports marginal effects. Standard deviations are in brackets.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 8
Heterogeneous role of informal borrowing in mortgage access, mortgage demand, and housing demand.

	(1) *D_mortgage*	(2) *LTV*	(3) *D_area*	(4) *D_unit price*
First stage of lninformal	Yes	Yes	No	No
Financial Development 1				
lninformal	−0.0100**	−0.0142***	1.209**	2.560***
	(0.0223)	(0.0208)	(0.522)	(0.395)
lninformal × D_avedtgdp	0.0029**	0.0030**	−0.871*	−1.408***
	(0.0070)	(0.0068)	(0.525)	(0.384)
lnmortgage			−1.590**	−1.309**
			(0.584)	(0.444)
Financial Development 2				
lninformal	−0.0242***	−0.0303***	3.047**	3.405***
	(0.0265)	(0.0243)	(1.313)	(0.997)
lninformal × patm	0.0140***	0.0156***	−1.951*	−1.512*
	(0.0156)	(0.0151)	(1.177)	(0.894)
lnmortgage			−1.754**	−1.293**
			(0.586)	(0.447)
Financial Development 3				
lninformal	−0.0248***	−0.0309***	4.431**	3.831**
	(0.0290)	(0.0267)	(1.591)	(1.206)
lninformal × pbank	0.0122***	0.0138***	−2.726**	−1.530*
	(0.0159)	(0.0155)	(1.194)	(0.905)
lnmortgage			−1.616**	−1.352**
			(0.587)	(0.445)
Control variables	Yes	Yes	Yes	Yes
N	8491	8491	2758	2758

Note:
Control variables include basic household information such as income, age, age squared, gender, educational background and occupation, marriage status of the household head, share of young and elderly members of all household members, and time and regional fixed effects.
Columns (1) and (2) report marginal effects; columns (3) and (4) report OLS coefficients. Standard deviations are in brackets.
* $p < 0.1$
** $p < 0.05$.
*** $p < 0.01$.

As shown in Table 9, neither the interaction term $lninfomal \times D\_risker$ nor $lninfomal \times literacy$ is significant, which suggests that there is no significant impact of household risk aversion on the correlation between social capital and informal borrowing. The results is consistent with current literature (Boucher and Guirkinger, 2007), providing evidence that the implicit cost of social capital is generally ignored by urban Chinese households.

4.4.3. Income levels and uncertainty

Compared with the high-income group, the low-income group faces more credit rationing and may be more dependent on informal channels to finance its borrowing (Khoi et al., 2013). To test this, we divide the whole sample into two low-income and high-income groups according to their income levels. We introduce interaction terms between the informal borrowing amount and the income group dummy

Table 9
Risk attitude, financial literacy and informal borrowing.

	(1) *D_mortgage*	(2) *LTV*	(3) *D_area*	(4) *D_unit price*
First stage of lninformal	Yes	Yes	No	No
Risk Attitude				
lninformal	−0.0082*	−0.0125**	0.485*	1.958***
	(0.0224)	(0.0210)	(0.542)	(0.411)
lninformal × D_risk	−0.0012	−0.0007	1.661	−0.286
	(0.00826)	(0.0079)	(1.015)	(0.770)
lnmortgage			−1.699**	−1.412**
			(0.586)	(0.444)
Financial Literacy				
lninformal	−0.0086*	−0.0128**	0.983*	1.583***
	(0.0226)	(0.0211)	(0.524)	(0.397)
lninformal × literacy	−0.0003	−0.0002	−0.0614	0.593
	(0.00698)	(0.00660)	(0.501)	(0.380)
lnmortgage			−1.719**	−1.393**
			(0.586)	(0.444)
Control variables	Yes	Yes	Yes	Yes
N	8491	8491	2758	2758

Note:
In this table, all of the cross terms are exclusively controlled in different regressions. For simplicity, we only report these cross terms and put them jointly in the coefficient matrix as Table 6.
Control variables include basic household information such as income, age, age squared, gender, educational background and occupation, marriage status of the household head, share of young and elderly members of all household members, and time and regional fixed effects.
Columns (1) and (2) report the marginal effects; columns (3) and (4) report OLS coefficients. Standard deviations are in brackets.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

variables to check whether informal borrowing is more important for any specific income group. Similarly, households with greater income uncertainty might have greater difficulty accessing formal borrowing and may thus be more dependent on informal channels (Struyk and Patel, 2009). We follow Diaz-Serrano (2005) horizontal comparison method to measure income uncertainty.[11] We classify high income uncertainty households and low income uncertainty households according to the median level of income uncertainty and introduce its interaction term with the amount of informal borrowing to the models. However, we do not find significant variations in income levels or income uncertainty. Thus, it seems that the effect of informal borrowing is less related to individual income conditions.[12]

5. Conclusion

In this paper, we provide a new explanation for the co-existence of huge housing demand and low dependence on mortgage loans in urban China, focusing on the effect of households' informal borrowing from relatives and friends. The empirical analysis based on household surveys suggests that because of the low financial cost of informal borrowing, households tend to borrow as much as possible from informal channels until they reach the constraint set by their social capital. This informal borrowing will crowd out formal borrowing such as mortgage loans from commercial banks in terms of both the probability of obtaining a loan and the loan amount. Additionally, controlling for other factors, households with more social capital and thus more capacity to borrow from informal channels will have higher housing demand. We find that these effects are especially important in cities with less mature financial systems.

Our results have several policy implications. Most importantly, because of the existence of informal borrowing and the relatively less important role of formal borrowing, even if the Chinese housing markets do witness a major correction in the near future, it is much less likely to trigger the collapse of the financial sector as in the 2008 subprime lending crisis in the United States. In contrast, it is more likely to substantially affect the household sector in China, which might also result in widespread economic and social effects. Accordingly, research that considers the patterns of default behavior in informal borrowing may be particularly important. We leave this to future research.

[11] In the first step, we estimate the income function using work experience, education level, gender, occupation, and other types of explanatory variables according to human capital theory (Mincer, 1958; Musgrove, 1979). In the second step, we calculate the ratio of the residual of the first step to the absolute level of household income as a measure of income uncertainty.

[12] To save space, we do not show the results of the income level regression or the income uncertainty regression. More detailed regression results are available upon request.

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