Housing wealth effect in China

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Preliminary draft, 12 March 2025

Abstract

We estimate the effects of changes in house prices on consumption using a unique dataset of Alipay transactions from Chinese households, spanning January 2018 to April 2023. We find significant housing wealth effects: a 10% increase or decrease in housing prices leads to a 1.9% increase or decrease in consumption across 42 Tier 1 and Tier 2 cities. These effects, which are concentrated in the consumption of services and non-durable goods, appear larger for Alipay users over 40 years old—among whom there is a higher proportion of homeowners. We also find that housing wealth effects are much less homogeneous across Tier 3 cities. In the top 20 richest Tier 3 cities, the housing wealth effects is estimated to be comparable to one estimated for the Tier 1 and 2 cities. But the wealth effects are not precisely estimated for the entire group of Tier 3 cities.

Keywords: Consumption, Housing price, Savings.
JEL classification: R2; R3

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1 Introduction

One of the biggest risks to Chinese economic activity is the housing market (see Rogoff and Yang (2022)). House prices and the debt of Chinese residents have increased by 49% and 23% respectively from 2015 to 2021. This puts the Chinese economy at risk of a debt deflation downward spiral reminiscent of well documented boom bust cycles (Fisher (1933);Sufi (2023)).

However, little is known of the strength of the effects of changes in house prices on Chinese consumption. For a start these effects are hard to trace at the macroeconomic level with macroeconomic data. Indeed, macroeconomic time series for any given country, including China, have too few degrees of freedom to disentangle wealth effects from other forces that typically impact both house prices, economic activity and consumption. Very few studies have used micro data to estimate house wealth effects in China. Waxman et al. (2020) used credit card data for FF households from 2011 to 2013. While they found that increases in house prices crowd out consumption their estimates may be partially outdated because the proportion of homeowners in China increased considerably over the last decade.

Knowledge on the qualitative and quantitative effects of house prices on consumption in China is very limited. This paper contributes to fill this knowledge gap. We presents estimates of house wealth effects on Chinese consumption that harness a unique dataset. We analyse Alipay monthly transactions Chinese households from 2018 to 2023. We decompose Alipay purchases in services, non-durables and durables consumption. We also observe the geographical location of users, their age, (gender) while we use levels of consumption across users as indicators of their income level. Even more critical is knowing where Alipay users live and consume. We use the cross-section variance in house prices, across about 100 cities to assess whether and by how much house prices impact the consumption of these cities' residents. We can also control for other determinants of consumption that vary across cities

in our data: economic activity indicators and credit aggregates which are available at the city or the provincial level.

We find a significant housing wealth effect in Tier 1 and Tier 2 cities: a 10% increase or decrease in housing prices leads to a 1.9% increase or decrease in consumption. These effects are more pronounced for households above 40 years old and homeowners. We also find that housing wealth effects are much less homogeneous across Tier 3 cities. In the top 20 richest Tier 3 cities, the housing wealth effects is estimated to be comparable to one estimated for the Tier 1 and 2 cities. But the wealth effects are not precisely estimated for the entire group of Tier 3 cities. This is similar to the macroeconomic data. During the downturn in the real estate market in 2024, the decline in consumption in first- and second-tier cities is more significant compared to third-tier cities.

The rest of the paper is structured as follows. Section 2 reviewed the literature. Section 3 describes the institutional background of Alipay, the data construction, and the variables used in the paper. Section 4 illustrates the identification strategies and reports the empirical results. Section 5 concludes

2 Related literature

First, our paper contributes to the broad literature discussed how consumption responds to changes in housing prices. In the US, the house wealth effect has been well established, with several empirical studies identifying a significant positive relationship between housing appreciation and consumption (DeFusco (2018); Aladangady (2017); Mian et al. (2013)). (TBC with evidence available for other countries) However, whether similar wealth effects prevail in China is actively debated. Sufi (2023) argues such effects need not operate in China because Chinese households are shill unable to use home equity to obtain credit for consumption, nor can they refinance their mortgage debt for cash-out refinancing for consumption purposes

(Chen et al. (2020)). In addition, some of the empirical evidence (Waxman et al. (2020)) demonstrates a large and negative housing price elasticity of consumption in China. Using a unique dataset from Alipay, we provide evidence that both the wealth effect and crowding out effects during the last 5 years. While we estimate wealth effects to have been large in Tier 1 and Tier 2 cities, crowding out effects still prevail in Tier 3 and Tier 4 cities.

Second, our paper contributes to the literature focuses on the real estate markets in China, which plays a significant role in the country's economy (Liu and Xiong (2018)). Housing prices have experienced a dramatic and prolonged boom throughout China, raising concerns among academics and policymakers about the emergence of a potential housing bubble that could harm China's financial system and economy, leading to misallocation and reduced consumption (Wu et al. (2012); Chen and Wen (2017); Glaeser et al. (2017); Song and Xiong (2018)). However, after the implementation of strict regulatory policies in 2020, the Chinese property market experienced a significant slowdown, coinciding with a weakening in consumption. Furthermore, the imbalances between supply and demand for housing stock is particularly pronounced in Tier 3 cities, which are generally smaller and where households have, on average, lower income levels than those who live in Tier 1 and Tier 2 cities. (Rogoff and Yang (2022)). In this paper, we highlight an important difference across China's real estate markets. The effects of housing prices on consumption since 2018 have been positive only in Tier 1 and Tier 2 cities. In Tier 3 and Tier 4 cities, our estimates show that crowding out prevailed over the same period.

Third, our paper also contributes to the literature by employing digital payment data to address macroeconomic questions. Chapman and Desai (2023) offered an evidence to show the payments systems data can assist in estimating the state of the economy in real time. Traditional consumption data often relies on surveys, which can have low timeliness. Our research uses one of the largest payment datasets, Alipay, to track consumption information. This offers the advantage of high data accuracy and timeliness, updated until May 2023,

allowing for a more up-to-date reflection of the impact of recent changes in China's real estate market on consumption.

3 Data and Institutional Background

3.1 Alipay e-wallet

The use of e-wallets has witnessed remarkable growth, particularly in Asia. In 2021, e-wallets were used for 69% of e-commerce spending and 44% of point-of-sale transactions in the Asia-Pacific region. The large use can be attributed to several factors, including underdeveloped payment infrastructures, a significant portion of the population remaining unbanked, and rapidly expanding e-commerce markets. E-wallet 'super-apps' such as Alipay in China, Grab in Singapore, and Paytm in India have been at the forefront of this revolution.

In China, e-wallets have become a cornerstone of household consumption. Founded in 2004, Ant Group's Alipay has developed a multifaceted ecosystem encompassing a broad spectrum of services. The platform adeptly integrates financial transactions with daily activities such as online shopping and food delivery. It offers a seamless user experience by consolidating these services into a single 'super-app.' By 2021, e-wallets had emerged as the predominant payment method for e-commerce transactions, commanding an 83% market share. In this landscape, Alipay and WeChat Pay are the leading e-wallets in China, exemplifying the nation's rapid adoption and reliance on digital payment solutions.

3.2 User-level data

We have access to comprehensive data encompassing individual monthly consumption and demographic information from Alipay users, gathered through the China Household Wealth Survey by the China Household Finance Survey and Research Center at Southwestern Uni-

versity of Finance and Economics, in collaboration with the Ant Group Research Institute. This dataset includes detailed consumption information from Alipay, as well as data on whether users are homeowners or renters, their locations, and other demographic details. We specifically selected active Alipay users, defined as those whose monthly expenses on Alipay exceed 100 RMB. This criterion helps to exclude users for whom Alipay is not a primary consumption tool, thereby enhancing the representativeness of the sample in terms of consumption behavior.

Table 2 presents detailed consumption and demographic information for the users in our sample. Among these individuals, 30% are female, with an average age of 33 years, indicating that Alipay users tend to be from younger generations. The average monthly consumption is approximately 5900 RMB (around 600 USD).

There are several advantages to using digital payment data. Firstly, it represents actual transaction activity, ensuring the accuracy of both the amount and type of consumption, and provides more timely updates and higher data frequency compared to survey data. Our access extends up to April 2023, making it one of the most current datasets available. Secondly, digital payments are more inclusive than traditional survey data and transaction data from credit and debit cards, reaching populations that are more transient and those with lower incomes who may not qualify for credit cards. Thirdly, user-level data allows for more detailed heterogeneous analysis and better control of individual factors affecting consumption, compared to macro-level regional data.

However, there are limitations to consider with the data structure. First, While digital payments are crucial in retail consumption, they represent only a portion of total consumption and may not fully capture overall consumption trends. Second, Figure 1 illustrates the positive correlation between Alipay consumption growth and total consumption growth on a year-over-year basis at the city level. To enhance the representativeness of our data, we have excluded some tier 3 cities with official annual consumption growth rates below 0.3.

Additionally, we applied winsorization to the data by removing the top 5% of consumers in terms of level of expenditure in Alipay to prevent outliers from skewing the results.

3.3 City-level information

The city-level information includes housing prices, GDP per capita, and the leverage ratio. The housing price data are sourced from the 100-city housing price index published by the China Index Academy and included in the WIND database. This index reflects a wide range of housing types, including commercial properties, villas, and affordable housing, encompassing all saleable houses with a sales license. The leverage ratio is calculated as the total annual loans divided by the city-level GDP. It is important to note that there are significant differences between Tier 1&2 cities and Tier 3&4 cities. Specifically, there has been a substantial decline in housing prices observed in Tier 3&4 cities, as depicted in Figure 2. Third, because we need to incorporate information on both renters and homeowners, we rely on survey data. Although the survey recipients are randomly selected, the participants who choose to respond are not. To address this issue, we conduct a double check on a randomly selected sample.

3.4 Instrument variables

We employ instrumental variables for housing prices to address endogeneity issues. We use the housing price from the previous month as an instrument variable, considering that the consumption of individual Alipay users have limited impact on city-level housing prices with a one-month lag. Additionally, we add the lagged land supply from one year ago and its interaction with mortgage rates to our set of instrumental variables. In China, the local government holds significant influence over housing prices through their control of land supply. (TBC)

4 Empirical Evidence

4.1 Identification Strategy

Our analysis starts with a simple model that analyses the main determinants of credit. We consider the following baseline model:

$$ln(consumption)_{it} = \alpha_i + \beta_1 \cdot ln(houseprice)_{c(i)t} + X_{c(i)t} + \varepsilon_{it} \quad (1)$$

where i and t indicate individual and the specific year-month. The $ln(consumption)_{it}$ stands for the log change in a series of digital consumption via Alipay of individual i from month t to t+1. $ln(houseprice)_{c(i)t}$ is house price of of city c where individual i is located in month t.$X_{c(i)t}$ is the control variables of city c , including logarithm of GDP per capita and leverage ratio. α_i represents individual fixed effect and ε_{it} is the error term. Standard errors are clustered at the account level. Depending on the specification, an estimate of β_1 captures the elasticity of the consumption growth rate to changes in the house prices.

4.2 Baseline Results

Table 2 presents the results of equation (1), which employs instrumental variables. In Tier 1 and Tier 2 cities, consumption is positively correlated with housing prices; a 10% increase in housing prices leads to a 1.9% increase in consumption. Given the correlation of Alipay consumption data with official statistics on consumption at the city level is of the order of 0.15 (see figure 1), this means that a a 10% increase in housing prices leads to a 0.3% increase in consumption at the city level. This magnitude appears in line with available estimates for advanced economies. Mian et al. (2013)

In contrast, in Tier 3 and Tier 4 cities, the effects of housing prices on consumption are not precisely estimated. There are several reasons for the differing effects of housing prices

on consumption across city tiers. First, as we show later, in the top 20 Tier 3 cities in terms of per capita income, our estimates of the the housing wealth effects are qualitatively similar to the one we estimate for Tier 1 and 2 cities. Second, taking a supply side perspective, housing prices are negatively correlated with the oversupply of housing in Tier 3 and Tier 4 cities. In recent periods, declines in house prices could signal that the oversupply is shrinking, leading households that own property to feel paradoxically richer and thus consume more. Third, taking a demand side perspective, Chinese cities differ considerably in terms of their demographic dynamics. There is a large population outflow from Tier 3 and Tier 4 cities. Population growth in Tier 3 cities, already flat or slightly negative prior to the pandemic, declined by 2% in 2021. Meanwhile, Tier 1 and Tier 2 cities saw increases of 7.2% and 0.2%, respectively. These demographic trends may impact households assessment of the future value of houses.

4.3 Baseline weighted by national age distribution

Since Alipay users are predominantly from younger generations, there could be a bias in the results. This outcome is more likely to represent the consumption response of young people in China. For example, the insignificant results in Tier 3 cities may be due to the fact that younger individuals are less likely to own property, thus lacking a wealth effect. To address this issue, we adjusted our sample by weighting it according to the age distribution of the Chinese population.

Table 3 presents the adjusted results. We can see that a 10% increase in housing prices leads to a 2.9% increase in consumption, indicating that the wealth effect is more pronounced when considering older age groups. This is consistent with the fact that older individuals are more likely to own property. On the other hand, the results for Tier 3 and Tier 4 cities remain insignificant, suggesting that even after adjusting for population age, the wealth effect in these cities is still not significant.

4.4 Age differences

We further consider the differences in age. Older individuals, who are more likely to be homeowners, should exhibit stronger consumption responses to changes in housing prices, while younger households may have less pronounced or even negative responses. In Table 4, we present regression estimates for different age cohorts. In Tier 1 and Tier 2 cities, we observe a stronger wealth effect among older cohorts compared to younger ones. A 10% increase in housing prices corresponds to a 3.2% increase in total non-housing spending for older users, while the effect is not significant for younger users.

However, in Tier 3 and Tier 4 cities, the wealth effect is less pronounced for older cohorts compared to those in Tier 1 and Tier 2 cities. Additionally, a 10% increase in housing prices results in a 2.0% reduction in non-housing spending for younger individuals, possibly due to higher housing prices relative to reasonable levels in these cities.

4.5 Home owner vs Renter

Furthermore, we examined the differences between homeowners and renters. Using survey data from Alipay users, we can identify whether they own property. For residents in Tier 1 & 2 cities, we find that housing prices do not have a significant impact on renters. This may be because many residents in these cities are only working there and may have purchased property in their hometowns. However, for homeowners, we observe a significant wealth effect; a 10% increase in housing prices corresponds to a 2.32% increase in total non-housing spending.

In contrast, for renters in Tier 3 and Tier 4 cities, we find a notable crowding-out effect; a 10% increase in housing prices results in a 2.0% reduction in non-housing spending. For homeowners in these cities, the impact is not significant. This could be due to the oversupply of housing in Tier 3 and Tier 4 cities, making it more difficult to sell properties.

4.6 Top tier 3&4 cities

In order to better understand why housing wealth effects in Tier 3 and Tier 4 cities are imprecisely estimated we considered various sub-samples estimations.We selected the top 30% of Tier 3 cities with the highest per capita GDP (about 20 cities). These cities, although classified as Tier 3, are relatively economically developed and have a higher attraction for population inflows.

In these more affluent Tier 3 cities, we observe a wealth effect similar to that in Tier 1 and Tier 2 cities. A 10% increase in housing prices leads to a 1.5% increase in consumption. Additionally, for renters, we observe a crowding-out effect similar to that in other Tier 3 cities, while the wealth effect is primarily concentrated among homeowners. This suggests that the wealth effect is more pronounced in more affluent cities in China.

4.7 Random Sample

There is an issue with our sample in that we rely on survey data to obtain information on "renters or homeowners", which is not included in the typical Alipay data. The survey sample may introduce bias, as some individuals may not respond to the survey. For example, respondents may be more concentrated in first- and second-tier cities or among higher-spending users, which could affect the results. To address this issue, we randomly selected an additional 100,000 Alipay users to ensure the sample's representativeness. Since some Alipay users might use their accounts for business purposes, we applied a 5% winsorization to the sample to exclude commercial and inactive users.

We also conducted sub-sample regressions on the random sample, with the results presented in Table 7. The findings are similar to those from the survey sample. In first- and second-tier cities, we observed a strong wealth effect: a 10% increase or decrease in housing prices leads to a 2.9% increase or decrease in consumption. However, the impact is not signif-

icant in third-tier cities. Furthermore, among the top 30% of third-tier cities, we also found a wealth effect, where a 10% increase or decrease in housing prices leads to a 1.8% increase or decrease in consumption, which is smaller compared to first- and second-tier cities. These results indicate that the findings based on the survey sample are robust and not altered by changes in the sample.

5 Conclusion

The impact of house prices on consumption is a key question for understanding China's economic development. By leveraging a unique dataset of Alipay transactions from 100,000 Chinese households covering the period from January 2018 to April 2023, we estimate the effects of changes in house prices on consumption in China. We find significant housing wealth effects, but only in Tier 1 and Tier 2 cities and in the 20 most affluent Tier 3 cities. In contrast, across a larger group of Tier 3 cities, the effects of changes in house prices do not have a statistically significant impact on consumption. This may be due heterogeneity across Tier 3 cities. For some of these oversupply of real estate, economic underdevelopment, population outflows, and weak demand may prevail in households perception of genuine value of housing property.

These findings indicate that China should tailor public policies on real estate to the specific issues of each category of cities. Sustaining housing prices outside of Tier 1&2 cities need not spur consumption unless it reflects a policy that helps clear oversupply.

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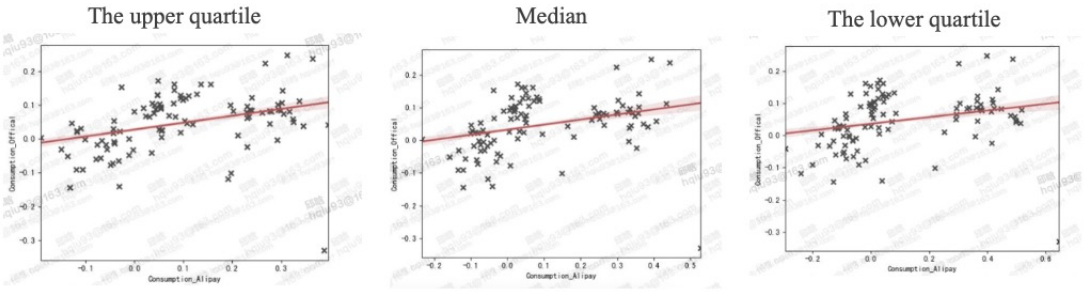
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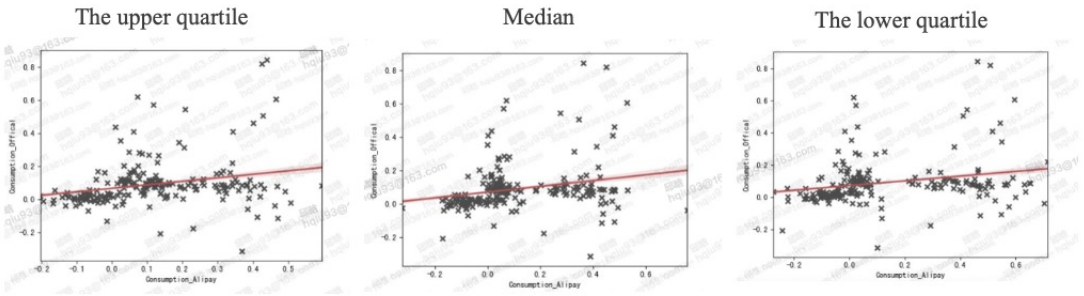
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(a) Tier 1&2

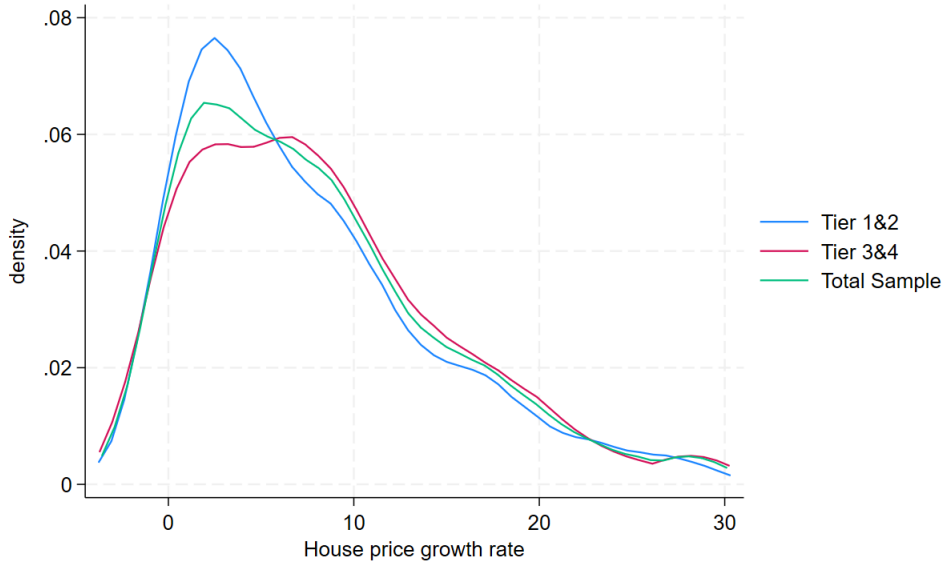


(b) Tier 3&4

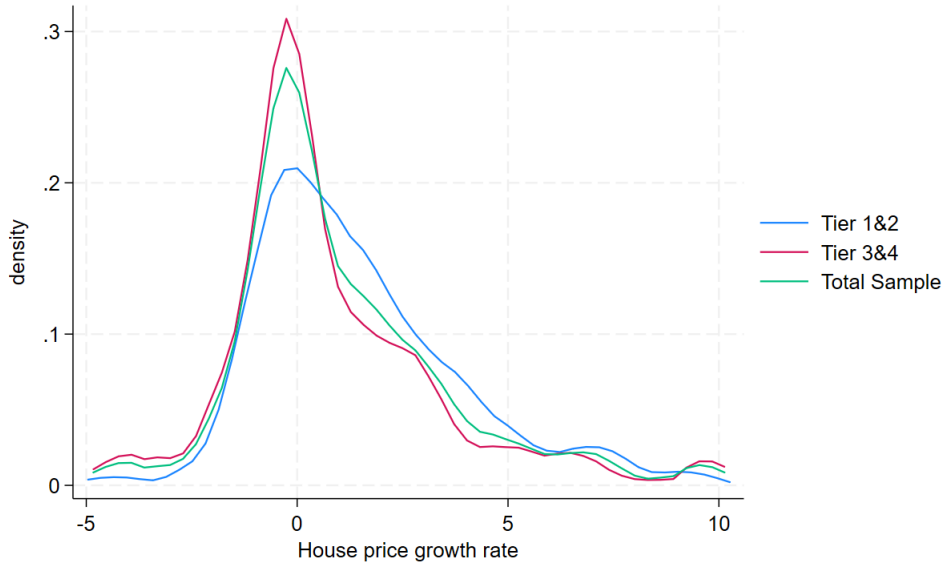
Figure 1: Alipay consumption vs official consumption

Data source: CEIC; Ant Group

Notes: The sample period is from January 2018 to April 2023 and the sample includes 42 Tier 1&2 cities and 52 Tier 3&4 cities. The unit of observation is city-year. For each city, we calculated the 75th percentile, median, and 25th percentile of Alipay users' consumption, and then computed the growth rates. These growth rates serve as the variables on the x-axis, while the y-axis represents the official annual retail sales growth. For the growth rate in 2020 and 2021, we used the average annual growth rate from 2019 to 2021.



(a) 2018-2020



(b) 2021-2023

Figure 2: House price growth rate among cities

Data source: WIND

Notes: This graph presents the distribution of annual house price growth rates. Panel (a) shows the distribution for the period 2018-2020, while Panel (b) shows the distribution for the period 2021-2023. The blue line represents Tier 1 and Tier 2 cities, the red line represents Tier 3 and Tier 4 cities, and the green line represents the overall sample.

Table 1: Summary Statistics

	N	Mean	St. Dev	P25	Median	P75
Tier 1&2						
Consumption (RMB)	1121239	5934	17836	1245	2594	5560
Age	1121239	34.81	8.98	28	33	40
Gender (Male=0, Female=1)	1121239	0.32	0.46	0	0	1
Housing prices (RMB)	1121239	24633	16033	11383	14670	42487
Leverage ratio	1121239	2.28	0.46	1.99	2.18	2.47
GDP per capita (log)	1121239	11.7	0.308	11.4	11.8	11.9
Tier 3&4						
Consumption (RMB)	647896	5887	28166	1050	2238	4941
Age	647896	34.47	8.14	28	33	39
Gender (Male=0, Female=1)	647896	0.28	0.45	0	0	1
Housing prices (RMB)	647896	13445	4283	8124	10694	14302
Leverage ratio	647896	1.36	0.42	0.94	1.32	1.65
GDP per capita (log)	647896	11.19	0.35	11.00	11.23	11.44

Notes: The sample period is from January 2018 to April 2023 and the sample includes 42 tier 1&2 cities and 52 tier 3&4 cities. Housing price is at the city-month level. Leverage ratio is calculated as the total bank loans divided by GDP at the city-year level. GDP per capita (log) is the logarithm of per capita GDP at the city-year level.

Table 2: Baseline using IVs

	Consumption	
	Tier 1&2	Tier 3&4
House price (IV)	0.194***	-0.042
	(0.056)	(0.062)
Leverage ratio	0.026	-0.015
	(0.035)	(0.028)
GDP per capita (log)	0.009	-0.223
	(0.064)	(0.073)
Observation	1121239	647896
User fixed effects	Yes	Yes
Year-month fixed effects	Yes	Yes

Notes: The sample period is from January 2018 to April 2023 and the sample includes 42 tier 1&2 cities and 52 tier 3&4 cities. The unit of observation is user-month. Housing price is instrumented at the city-month level. Leverage ratio is calculated as the total bank loans divided by GDP at the city-year level. GDP per capita (log) is the logarithm of per capita GDP at the city-year level. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the year-month level and are shown in parentheses.

Table 3: Baseline weighted by national age distribution

	Consumption	
	Tier 1&2	Tier 3&4
House price (IV)	0.298***	0.023
	(0.086)	(0.073)
Leverage ratio	-0.023	-0.017
	(0.057)	(0.037)
GDP per capita (log)	0.119	-0.035
	(0.065)	(0.075)
Observation	934568	539320
User fixed effects	Yes	Yes
Year-month fixed effects	Yes	Yes

Notes: The sample period is from January 2018 to April 2023 and the sample includes 42 tier 1&2 cities and 52 tier 3&4 cities. The unit of observation is user-month. Housing price is instrumented at the city-month level. Leverage ratio is calculated as the total bank loans divided by GDP at the city-year level. GDP per capita (log) is the logarithm of per capita GDP at the city-year level. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the year-month level and are shown in parentheses.

Table 4: Among different groups of age

	Tier 1 & 2			Tier 3& 4		
	Age $\leq$ 30	30 $<$ Age $<$ 40	Age $\geq$ 40	Age $\leq$ 30	30 $<$ Age $<$ 40	Age $\geq$ 40
All instrument variables						
House price (IV)	0.086	0.252***	0.328***	-0.175**	-0.069*	0.206**
	(0.069)	(0.073)	(0.007)	(0.065)	(0.079)	(0.094)
Leverage ratio	0.108***	-0.028	-0.105**	0.027	0.078*	-0.279***
	(0.034)	(0.043)	(0.049)	(0.042)	(0.040)	(0.064)
GDP per capita (log)	0.173**	-0.203**	-0.029	-0.266**	-0.015***	-0.569***
	(0.075)	(0.088)	(0.105)	(0.123)	(0.090)	(0.155)
Observation	403382	467646	250205	231207	284120	138484
User fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The sample period is from January 2018 to April 2023 and the sample includes 42 tier 1&2 cities and 52 tier 3&4 cities. The unit of observation is user-month. Housing price is instrumented at the city-month level. Leverage ratio is calculated as the total bank loans divided by GDP at the city-year level. GDP per capita (log) is the logarithm of per capita GDP at the city-year level. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the year-month level and are shown in parentheses.

Table 5: Home owner vs Renter

	Tier 1 & 2		Tier 3 & 4	
	Renter	Owner	Renter	Owner
All instrument variables				
House price (IV)	0.069	0.237***	-0.203**	-0.0163
	(0.077)	(0.063)	(0.081)	(0.068)
Leverage ratio	0.043	0.014	0.033	-0.026
	(0.043)	(0.039)	(0.064)	(0.032)
GDP per capita (log)	-0.050	0.011	-0.211***	-0.225**
	(0.130)	(0.064)	(0.137)	(0.076)
Observation	186069	935849	97941	550570
User fixed effects	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes

Notes: The sample period is from January 2018 to April 2023 and the sample includes 42 tier 1&2 cities and 52 tier 3&4 cities. The unit of observation is user-month. Housing price is instrumented at the city-month level. Leverage ratio is calculated as the total bank loans divided by GDP at the city-year level. GDP per capita (log) is the logarithm of per capita GDP at the city-year level. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the year-month level and are shown in parentheses.

Table 6: Top tier 3 cities

	Top 30% tier 3&4 cities		
	All Sample	Renter	Owner
All instrument variables			
House price (IV)	0.154**	-0.367***	0.274***
	(0.073)	(0.145)	(0.075)
Leverage ratio	0.448	-0.110***	-0.568***
	(0.142)	(0.258	(0.149
GDP per capita (log)	0.048	-1.081**	-0.504
	(0.301)	(0.589)	(0.345)
Observation	234835	35108	201178
User fixed effects	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes

Notes: The sample period is from January 2018 to April 2023 and the sample includes 16 tier 3&4 cities. Top Tier 3 cities are selected as the top 30% of Tier 3&4 cities based on per capita GDP. The unit of observation is user-month. Housing price is instrumented at the city-month level. Leverage ratio is calculated as the total bank loans divided by GDP at the city-year level. GDP per capita (log) is the logarithm of per capita GDP at the city-year level. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the year-month level and are shown in parentheses.

Table 7: Baseline using random sample

	Consumption		
	Tier 1&2	Tier 3&4	Top Tier 3 cities
All instrument variables			
House price (IV)	0.287***	0.018	0.183***
	(0.056)	(0.047)	(0.076)
Leverage ratio	-0.032	-0.081**	-0.278**
	(0.037)	(0.037)	(0.123)
GDP per capita (log)	-0.171	0.216**	-0.895***
	(0.082)	(0.067)	(0.302)
Observation	783713	387625	135277
User fixed effects	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes

Notes: The sample period is from January 2018 to April 2023 and the sample includes 16 tier 3&4 cities. Top Tier 3 cities are selected as the top 30% of Tier 3&4 cities based on per capita GDP. The unit of observation is user-month. Housing price is instrumented at the city-month level. Leverage ratio is calculated as the total bank loans divided by GDP at the city-year level. GDP per capita (log) is the logarithm of per capita GDP at the city-year level. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the year-month level and are shown in parentheses.