BIS Working Papers

No 1319

Housing wealth effects in China

by Benoit Mojon, Han Qiu, Fang Wang and Michael Weber

Monetary and Economic Department

December 2025

JEL classification: R2, R3

Keywords: consumption, house prices, savings

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

Housing wealth effects in China *

Benoit Mojon † Han Qiu ‡ Fang Wang § Michael Weber ¶

2 December 2025

Abstract

We estimate the effects of changes in house prices on consumption using unique data of Alipay transactions from Chinese households, spanning from January 2017 to March 2023. We find significant housing wealth effects: changes in house prices are positively associated with future changes in consumption in 33 Tier 1 and Tier 2 cities. Specifically, in these cities, a 10% increase in house prices leads to a 1.6% increase in consumption. However, this relationship is not observed in smaller Tier 3 and Tier 4 cities. We also find that housing wealth effects are more pronounced among older households and homeowners, while renters show no such effect. Additionally, in Tier 3 and Tier 4 cities, higher house prices tend to crowd out consumption among younger households.

Keywords: Consumption, House prices, Savings.
JEL classification: R2; R3

*We thank Deniz Igan, Philip Wooldridge, Ilhyock Shim, Kang Shi (discussant) and participants at HKIMR-ECB-BOFIT Joint Conference on "Europe, Asia and the Changing Global Economy" and the seminar held at the Bank for International Settlements for useful comments and suggestions. The authors acknowledge and appreciate the supports from the Digital Economy Open Research Platform (www.deor.org.cn). All data was sampled and desensitized, and was remotely analyzed on the Ant Open Research Laboratory in an Ant Group Environment which is only remotely accessible for empirical analysis. The views expressed in this publication are those of the authors and do not necessarily reflect the views of the BIS or its member central banks. Fang Wang discloses an employment relationship in Ant Group. Ant Group did not exercise any influence on the content of this paper but has ensured confidentiality of the (raw) data.

†Bank for International Settlements. Email: `Benoit.Mojon@bis.org`

‡Bank for International Settlements. Email: `han.qiu@bis.org`

§Research Institute, Ant Group. Email: `fanfan.wf@antgroup.com`

¶Daniels School of Business, Purdue University, West Lafayette, IN, USA. Email: `weber366@purdue.edu`

1 Introduction

One of the most significant risks to Chinese economic activity stems from the housing market (Rogoff and Yang (2022)). Between 2015 and 2021, house prices and household debt in China rose by 49% and 23%, respectively, raising concerns about the potential for a debt-deflation spiral akin to the well-documented boom-bust cycles in economic history (Fisher (1933); Sufi (2023)). As the Chinese economy transitions towards a more consumption-driven growth model, the housing market plays a crucial role given that property constitutes a substantial share of household assets [1]. However, 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 housing wealth effects on Chinese consumption that harness a unique dataset. We analyse Alipay monthly transactions by 200,000 Chinese households from 2017 to 2023. The dataset includes information on users' geographical location, age, and gender. We leverage where Alipay users live and consume to relate the cross-section variance in house prices, across around 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 level.

We find significant housing wealth effects: changes in house prices are positively correlated with future changes in consumption across 33 Tier 1 and Tier 2 cities but not in the 66 Tier 3 and Tier 4 cities[2]. Although Tier 1 and Tier 2 cities are fewer in number, their economic contribution is substantial, accounting for over 37% of retail consumption, as shown in Figure 1. The presence of a significant housing wealth effect in Tier 1 and Tier 2

[1] According to a 2019 survey by the People's Bank of China, the assets of urban households in China are predominantly composed of physical assets, with housing accounting for nearly 70% of total assets and 74.2% of physical assets. The source article is accessible at here

[2] The definition of city tiers follows the classification by the National Bureau of Statistics of China, as presented in Table 1

cities underscores that a considerable portion—over 37%—of China's consumption is closely linked to the real estate market.

Our analysis reveals that housing wealth effects are stronger among older households, including those in Tier 3 and Tier 4 cities. However, the consumption of younger households in Tier 1 and Tier 2 cities is not significantly related to house prices. In contrast, in Tier 3 and Tier 4 cities, the consumption of younger households is crowded out by rising house prices (or crowded in by falling house prices). These findings shed an interesting new light on recent macroeconomic trends. During the real estate market downturn in 2024, the decline in consumption was more pronounced in Tier 1 and Tier 2 cities, where we estimate large and significant housing wealth effects, compared to Tier 3 and Tier 4 cities where we find little evidence of such effects.

We also find interesting contrasts across various demographic groups. In particular, the wealth effect in Tier 1 and Tier 2 cities is insignificant among younger individuals, while Tier 3 and Tier 4 cities exhibit a crowding-out effect for the youth, which echoes the findings of (Waxman et al. (2020)) across China for the 2011-2013 sample period. In contrast, older individuals experience a significant wealth effect across all city tiers. Similarly, when comparing homeowners and renters, only homeowners in Tier 1 and Tier 2 cities exhibit a significant wealth effect.

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

Our paper contributes to several strands of the literature. First, our paper relates to the broad literature on housing wealth effects. In the US, the housing 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)). 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 still 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 of both positive wealth effects, which prevail in Tier 1 and Tier 2 cities, and crowding out effects during among younger households in Tier 3 and Tier 4 cities. These findings differ from the view that housing wealth effects are absent in China. One reason is that, although Chinese households are unable to use home equity for borrowing, real estate functions as an investment asset for some residents. Consequently, a decline in house prices can result in asset devaluation, which may negatively impact household consumption. Additionally, a slowdown in the housing market, reflected in reduced transaction volumes, may further suppress consumption associated with housing upgrades and related expenditures.

Second, our paper contributes to the literature on real estate markets in China. These markets have had a central role in the country's macroeconomic developments in the last two decades (Liu and Xiong (2018)). Until 2020, house 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);Rogoff and Yang (2022)). However, after the implementation of strict regulatory policies in 2020, the Chinese property market experienced a significant slowdown, accompanied by a weakening in consumption. Furthermore, the imbalances between supply and demand for housing stock is particularly pronounced in Tier 3 and Tier 4 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 a significant difference across China's real estate markets. Since 2017, house prices have been correlated with future consumption only in Tier 1 and Tier 2. In contrast, house prices have shown no significant impact on consumption Tier 3 and Tier 4 cities. A possible explanation for this is the oversupply of housing in these smaller cities, which leads to lower liquidity and a weaker wealth effect.[3]

Third, our paper also contributes to the literature by employing digital payment data to address macroeconomic questions. Chapman and Desai (2023) showed how the payments systems data can help in estimating the state of the economy in real time. Traditional consumption data often relies on surveys, which can be less timely and prone to measurement error. Our research uses one of the largest payment datasets, Alipay, to track consumption information. Alipay data, along with other mobile payment data, has been widely used in the literature to study credit, consumption, and related topics (Hau et al. (2024); Xing et al. (2023); Agarwal et al. (2020)). The dataset in our paper is extensive enough to capture consumption patterns across samples of several hundred households in each city. Therefore, an advantage of our dataset lies in its heterogeneity with respect to an economic adjustment of interest—specifically, the varying local real estate market conditions across Chinese cities. Additionally, it encompasses diverse demographic groups and distinguishes

[3]According to Beike, a company primarily engaged in housing transactions and related services, a survey on housing vacancy rates in major Chinese cities shows an average of 7% in Tier 1 cities, 12% in Tier 2 cities, and 16% in Tier 3 cities.

between homeowners and renters.

3 Data and Institutional Background

3.1 Alipay e-wallet

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 University 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 characteristics.

In addition to this dataset, which we refer to as the "survey sample," we also randomly selected a "random sample" to address potential representativeness concerns of the survey sample, which relies on respondent participation. However, in the random sample, we are unable to observe whether users are homeowners or renters.[4]

There are several advantages to using digital payment data. First, 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 sample runs until March 2023, which is relatively recent compared to the literature. Second, 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. Third, user-level data enables the use of individual fixed effects to control for time-invariant factors that influence consumption.

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. The total survey sample consists of 103,335 users. After applying the criterion of monthly expenses exceeding 100 RMB, the sample size is reduced to 60,695 users. Since the sample includes monthly house prices for only 100 prefecture-level cities out of approximately 293 in China, the final dataset consists of 27,717 users.

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 34 years, indicating that Alipay users tend to belong to younger generations. The average monthly consumption is approximately 5,076 RMB (around 715 USD), while the median consumption is about 1,832 RMB (around 258 USD). Compared to official data for 2024, where the annual per capita consumption expenditure of residents nationwide is 28,227 RMB (approximately 3,976 USD), translating to a monthly average of 2,352 RMB (approximately 331 USD), it is

[4] This study was remotely conducted on the Ant Open Research Laboratory https://www.deor.org.cn/labstore/laboratory in an Ant Group Environment. All data was sampled and desensitized, and was analyzed on the Ant Open Research Laboratory. The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis and individual observations are invisible. The main regression variables include basic variables and consumption variables.

evident that the average consumption of Alipay users is significantly higher than the national monthly average, while the median consumption is roughly equal. One possible explanation for this discrepancy is that our sample is drawn from larger cities, where house prices and overall living costs are higher, leading to greater total consumption. Additionally, some high-value transactions made via Alipay have likely inflated the average of our measure of consumption expenditures paid by Alipay, contributing to the substantial difference between the mean and the median.

When analyzed by city tiers, the 25th, 50th (median), and 75th percentiles of consumption in Tier 1 and Tier 2 cities are higher than those in Tier 3 and Tier 4 cities. For instance, the median consumption in Tier 1 and Tier 2 cities is 2,596 RMB (around 366 USD), compared to 2,332 RMB (around 334 USD) in Tier 3 and Tier 4 cities. However, when looking at the average consumption, Tier 3 and Tier 4 cities surprisingly report higher figures. This is because the upper end of the consumption distribution in these cities surpasses that of Tier 1 and Tier 2 cities.

Finally, there are limitations to consider digital payments data. While they play a critical role in retail consumption, they account for only a portion of total consumption and may not entirely reflect overall consumption trends.

3.3 City-level information

The city-level information includes house prices, GDP per capita, and the Bank loan to GDP ratio. The housing price data is sourced from the China Index Academy. It is derived from the quoted prices of new residential properties across 100 major and well-developed cities in China. The data encompasses a diverse range of housing types, including commercial residential properties, villas, and affordable housing, and includes all saleable properties with government-issued sales licenses. Due to data limitations, we ultimately obtained data for 99 cities, which consist of 4 Tier 1 cities, 27 Tier 2 cities, and 66 Tier 3 cities and

Tier 4 cities. Table 1 provides the categorization of these cities. The Bank loan to GDP 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. Figure 2 illustrates the annual house price growth across Tier 1&2 cities and Tier 3&4 cities, divided into two periods: 2017–2020 and 2021–2023 March. From 2017 to 2020, most cities experienced positive house price growth, with an average growth rate of 6.5% and a median of 5.4%. However, from 2021 to 2023, growth rates shifted significantly downward, with many cities seeing price declines. The average growth rate dropped to 1.2%, and the median fell to 0.7%, largely due to the "Three Red Lines" policy introduced by the Chinese government in early 2021, which imposed strict debt limits on real estate developers to reduce financial risks. The impact was more severe in Tier 3 and Tier 4 cities, where the average growth rate plummeted from 6.9% to 1%, compared to a decline from 5.8% to 1.7% in Tier 1 and Tier 2 cities. In terms of retail consumption, the cities included in our sample collectively represent approximately 63% of China's total retail consumption as shown in Figure 1, underscoring the dataset's substantial representativeness and relevance for analysis.

3.4 Instrument variables

The dynamics of house prices and consumption respond to similar economic forces and endogenously influence one another. A key challenge for the estimation of housing wealth effect is reverse causality: rising house prices can boost consumption through the wealth effect, while higher consumption and economic growth can drive housing demand and prices. Additionally, omitted variables like macroeconomic conditions, policy changes, or demographic shifts can simultaneously influence both house prices and consumption. To address potential endogeneity concerns, we employ instrumental variables for house prices, specifically using lagged house prices (from the previous year) as an instrument. The rationale for using lagged house prices is twofold. First, regarding reverse causality, lagged house prices ensure that current individual consumption of Alipay users cannot plausibly exert a significant impact on city-level house prices from the previous year, effectively addressing concerns of reverse causality. Second, to mitigate potential omitted variable bias, where unobserved factors might simultaneously influence both lagged house prices and consumption, we control for local economic conditions in the regression. Additionally, to account for persistent and long-term unobserved factors, we include individual fixed effects in our analysis.

We also incorporate lagged local government fiscal revenues from one year prior, along with their interaction with mortgage rates, into our set of instrumental variables, following Gambacorta et al. (2023).

In China, land sales are controlled by local governments, and the concept of "land finance" is a critical component of the country's fiscal system. Local governments rely heavily on land sales as a primary source of fiscal revenue. When facing fiscal pressures, such as potential declines in revenue, local governments often resort to selling land to generate additional income. These land transactions significantly impact house prices, as they directly influence the availability and cost of land for development.

At the same time, mortgage rates, which are determined at the national level, affect housing markets differently across regions due to variations in land supply elasticity. In regions with limited land supply, where housing supply is relatively inelastic, changes in mortgage rates tend to have a more pronounced effect on house prices. Conversely, in regions with abundant land supply, where housing supply is more elastic, the impact of mortgage rate changes on house prices is less significant. This regional variation underscores the complex interplay between national mortgage policies and local land market dynamics in shaping house prices in China.

When controlling for economic variables such as GDP, lagged fiscal revenues primarily capture the financial conditions of local governments from the previous year, with their direct impact on current consumption likely being limited. Additionally, the interaction term further reduces the direct impact of the instrumental variable on consumption, as mortgage rates mainly influence the real estate market rather than directly affecting consumption behavior.

4 Empirical Evidence

4.1 Identification Strategy

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

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

where i and t indicate individual and the specific year-month. The $ln(consumption)_{it}$ stands for logarithm of digital consumption through Alipay for individual i in month t. $ln(houseprice)_{c(i)t}$ is the logarithm of the house price in 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 Bank loan to GDP ratio. α_i represents individual fixed effect and ε_{it} is the error term. Standard errors are clustered at the city-month 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 4 presents the results of equation (1) based on the survey sample, employing instrumental variables. The results of the first-stage regression are shown in Table 3. In Tier 1 cities and Tier 2 cities, consumption is positively related to house prices; a 10% increase in house prices leads to a 1.6% increase in consumption. This provides clear evidence to reject the null hypothesis that house prices have no impact on consumption in China.

In contrast, in Tier 3 and Tier 4 cities, the effects of house prices on consumption are not precisely estimated. There are reasons exists for the differing effects of house prices on consumption across city tiers. Taking a supply side perspective, house 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. 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 and Tier 4 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 household's assessment of the future value of houses. Households living in cities with more dynamic demography may give more prominence to housing as a reliable support of wealth than in cities where the population shrinks.

4.3 Wealth effects across age groups

We turn to consider the differences in housing wealth effects across demographics groups. Older individuals, who are more likely to be homeowners, should exhibit stronger consumption responses to changes in house prices, while younger households may have less pronounced or even negative responses. In Table 5, 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 house prices corresponds to a 2.9% increase in total non-housing spending for older users, while the effect is not significant for younger users. We also observe a significant wealth effect for older households in Tier 3 and Tier 4 cities, even if it smaller than for their counterparts in Tier 1 and Tier 2 cities. In addition, we find evidence of crowding out for consumption among the younger consumers in these smaller cities.

Since Alipay users are predominantly from younger generations, there could be a bias in the baseline estimates reported in Table 4. These are 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 6 presents results adjusted for Chinese demographics, specifically accounting for both gender and age distribution. We can see that a 10% increase in house prices leads to a 1.8% 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. However, even after increasing the weight of older individuals who experience a wealth effect in Tier 3 and Tier 4 cities, the results for these cities remain similar to our baseline estimates, suggesting that the wealth effect that our estimates unveil for older households is compensated by either no effect or crowding out effects for younger household.

4.4 Home owner vs renter

Furthermore, we examined the differences between homeowners and renters. The results are presented in Table 7. Using survey data from Alipay users, we can identify whether they own property. For residents in Tier 1 cities and Tier 2 cities, we find that house prices do not have a significant impact on renters. This may be because many residents in these cities are only working there and may not purchase property. However, for homeowners, we observe a significant wealth effect; a 10% increase in house prices corresponds to a 2.1% increase in total non-housing spending. In contrast, for homeowners in Tier 3 nad Tier 4 cities, the impact is not significant. This pattern could be due to the oversupply of housing in Tier 3 and Tier 4 cities.

4.5 Robustness with respect to the sample selection

Given our sample relies on survey data to obtain information on "renters" or "homeowners" status, which is not included in the typical Alipay data, we explored the robustness of our estimate in an alternative, random sample. Households data collected from this random sample includes another 100,000 households among Alipay users who did not necessarily answer the survey on home ownership. We also applied the criterion of spending at least 100 RMB per month to this database to ensure the representativeness of consumption behavior. As a result, our final sample consists of 52,893 users.

We then conducted sub-sample regressions on the random sample, with the results presented in Table 8. The findings are similar to those from the survey sample. In Tier 1 and Tier 2 cities, we observed a strong wealth effect: a 10% increase or decrease in house prices leads to a 2.6% increase or decrease in consumption, slightly higher than the one estimated with the Survey sample. However, the impact is again not significant across Tier 3 and Tier 4 cities. Altogether, these results indicate that the findings based on the survey sample are robust and not altered by changes in the sample.

4.6 Other robustness check

Given that the house prices in our sample are measured at the city level, while consumption is measured at the individual level, the standard errors may be downward biased. To address this potential issue, we aggregate the individual-level data to the city-month level. Additionally, to mitigate potential bias from cities with very few users, we restrict our analysis to cities with more than 300 users. The results are presented in Table 9. At the city-month level, house prices are positively associated with consumption in Tier 1 and Tier 2 cities, while the relationship remains insignificant in Tier 3 and Tier 4 cities. These findings are consistent with the baseline results obtained from individual-level data.

An increase in house prices could also influence the household consumption structure. One potential channel is that rising house prices may increase the operating costs of offline merchants, leading to higher prices for offline goods. As a result, consumers might shift toward online shopping, potentially increasing their usage of Alipay, which serves as a key payment tool for purchases on e-commerce platforms such as Taobao. To examine whether this phenomenon occurs in China, we analyze the impact of house prices on the share of offline consumption in total consumption. In China, Alipay facilitates both online consumption via e-commerce platforms and offline consumption via QR code payments. The results, presented in Table 10, We find that changes in house prices does not lead to a decline in offline consumption; on the contrary, there is a increase. This suggests that house prices have a limited impact on the consumption structure of Chinese residents. Consequently, any potential bias arising from this channel is likely to be minimal.

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 two samples of 100,000 Chinese households each, covering the period from January 2017 to March 2023, we estimate the effects of changes in house prices on consumption in China. Our findings reveal significant housing wealth effects, but only in Tier 1 and Tier 2 cities. In contrast, changes in house prices in Tier 3 and Tier 4 cities do not have a statistically significant impact on consumption. Factors such as an oversupply of real estate, economic underdevelopment, population outflows, and weak demand may influence households' perceptions of the genuine value of housing property, particularly in Tier 3 and Tier 4 cities.

From the perspective of demographic heterogeneity, the wealth effect in Tier 1 and Tier 2 cities is not significant among younger individuals, while in Tier 3 and Tier 4, the consumption of younger households appears to be crowded-out by higher prices of houses. However, for older individuals, a wealth effect is observed across all groups of cities. Similarly, when comparing homeowners and renters, only homeowners in Tier 1 and Tier 2 cities experience a significant wealth effect.

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

References

Sumit Agarwal, Wenlan Qian, Yuan Ren, Hsin-Tien Tiffany Tsai, and Bernard Yin Yeung. The real impact of fintech: Evidence from mobile payment technology. *Available at SSRN 3556340*, 2020.

Aditya Aladangady. Housing wealth and consumption: evidence from geographically linked microdata. *American Economic Review*, 107(11):3415–3446, 2017.

James TE Chapman and Ajit Desai. Macroeconomic predictions using payments data and machine learning. *Forecasting*, 5(4):652–683, 2023.

Kaiji Chen and Yi Wen. The great housing boom of china. *American Economic Journal: Macroeconomics*, 9(2):73–114, 2017.

Zhuo Chen, Zhiguo He, and Chun Liu. The financing of local government in china: Stimulus loan wanes and shadow banking waxes. *Journal of Financial Economics*, 137(1):42–71, 2020.

Anthony A DeFusco. Homeowner borrowing and housing collateral: New evidence from expiring price controls. *The Journal of Finance*, 73(2):523–573, 2018.

Irving Fisher. The debt-deflation theory of great depressions. *Econometrica: Journal of the Econometric Society*, pages 337–357, 1933.

Leonardo Gambacorta, Yiping Huang, Zhenhua Li, Han Qiu, and Shu Chen. Data versus collateral. *Review of Finance*, 27(2):369–398, 2023.

Edward Glaeser, Wei Huang, Yueran Ma, and Andrei Shleifer. A real estate boom with chinese characteristics. *Journal of Economic Perspectives*, 31(1):93–116, 2017.

Harald Hau, Yi Huang, Chen Lin, Hongzhe Shan, Zixia Sheng, and Lai Wei. Fintech credit and entrepreneurial growth. *the Journal of Finance*, 79(5):3309–3359, 2024.

Chang Liu and Wei Xiong. China's real estate market. 2018.

Atif Mian, Kamalesh Rao, and Amir Sufi. Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics*, 128(4):1687–1726, 2013.

Kenneth S Rogoff and Yuanchen Yang. A tale of tier 3 cities. Technical report, National Bureau of Economic Research, 2022.

Zheng Song and Wei Xiong. Risks in china's financial system. *Annual review of financial economics*, 10:261–286, 2018.

Amir Sufi. Housing, household debt, and the business cycle: An application to china and korea. Technical report, National Bureau of Economic Research, 2023.

Andrew Waxman, Yuanning Liang, Shanjun Li, Panle Jia Barwick, and Meng Zhao. Tightening belts to buy a home: Consumption responses to rising housing prices in urban china. *Journal of Urban Economics*, 115:103190, 2020.

Jing Wu, Joseph Gyourko, and Yongheng Deng. Evaluating conditions in major chinese housing markets. *Regional Science and Urban Economics*, 42(3):531–543, 2012.

Jianwei Xing, Eric Yongchen Zou, Zhentao Yin, Yong Wang, and Zhenhua Li. "quick response" economic stimulus: The effect of small-value digital coupons on spending. *American Economic Journal: Macroeconomics*, 15(4):249–304, 2023.

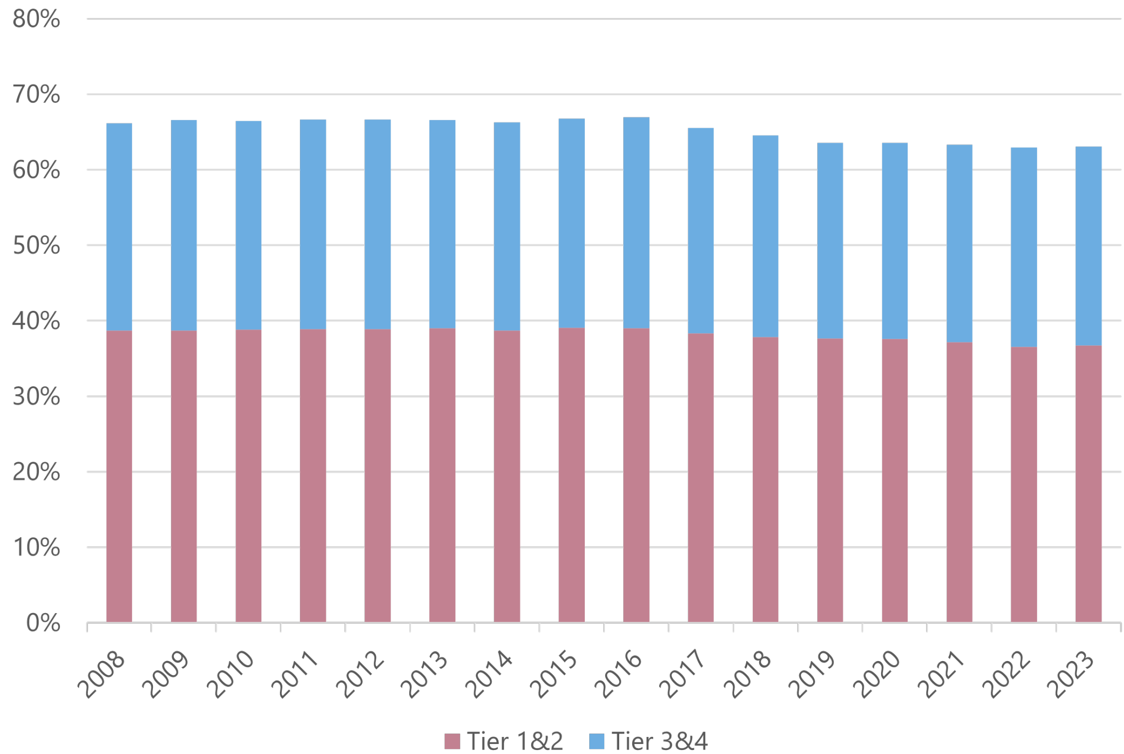
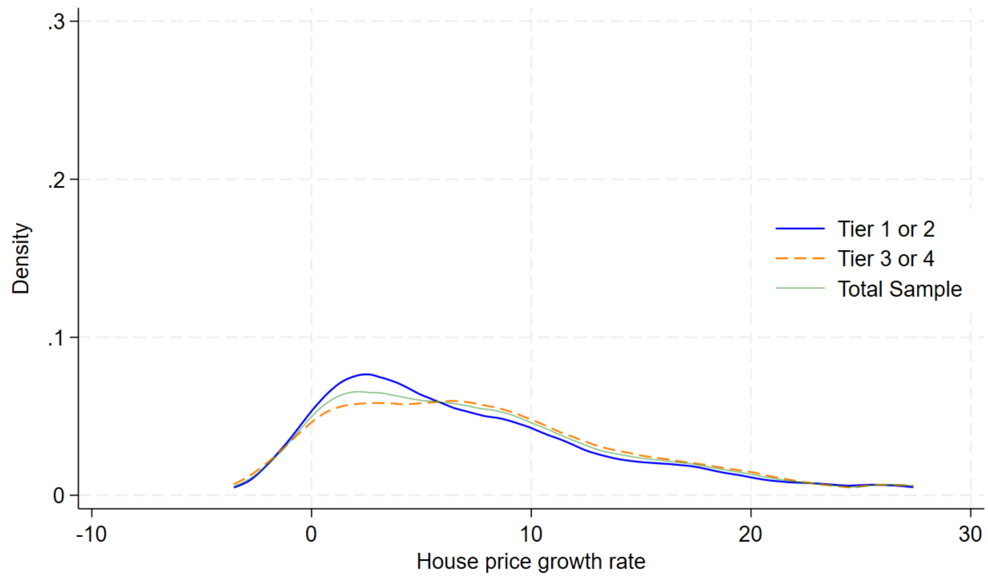


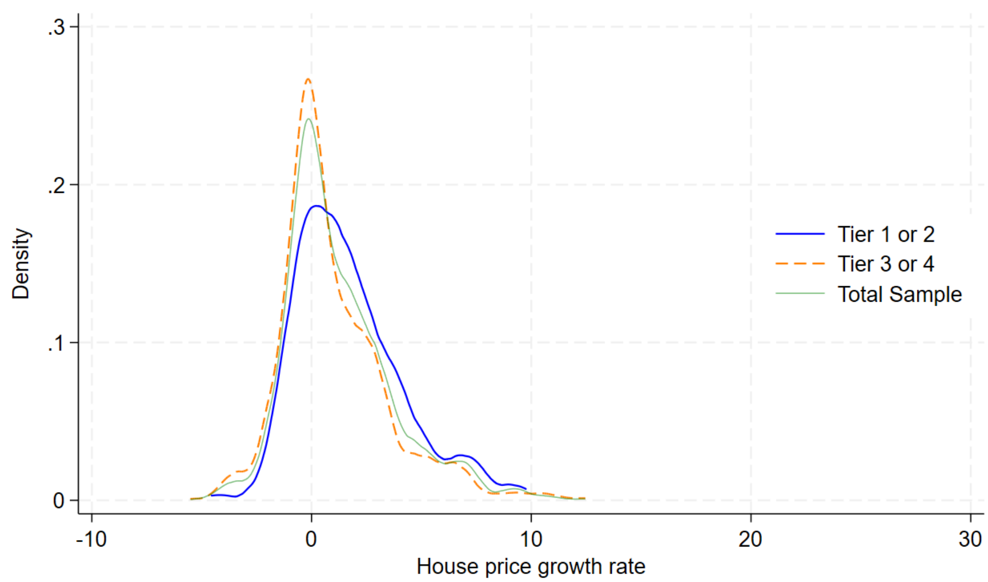
Figure 1: Retail consumption share of in cities within sample in China

Data source: CEIC

Notes: This graph illustrates the proportion of retail consumption in cities within our sample relative to the national total. The classification of Tier 1 and Tier 2 cities is based on the definition provided by the China National Bureau of Statistics. Due to missing data, we excluded Changshu, Zhangjiagang, Kunshan, Jiangyin, Nanchang, and Harbin. As a result, the graph includes 31 Tier 1 and Tier 2 cities, as well as 62 Tier 3 and Tier 4 cities.



(a) 2017-2020



(b) 2021-2023

Figure 2: House price growth rate among cities

Data source: China Index Academy

Notes: This graph presents the distribution of annual house price growth rates. Panel (a) shows the distribution for the period 2017-2020, while Panel (b) shows the distribution for the period 2021-2023 March. The blue solid line represents Tier 1 and Tier 2 cities, the yellow dotted line represents Tier 3 and Tier 4 cities, and the green solid line represents the overall sample.

Table 1: City Categorization Table

Category	**Cities (Count)**
Tier 1 Cities (4)	Beijing, Shanghai, Guangzhou, Shenzhen
Tier 2 Cities (29)	Tianjin, Shijiazhuang, Taiyuan, Hohhot, Shenyang, Dalian, Changchun, Harbin, Hangzhou, Ningbo, Hefei, Fuzhou, Xiamen, Nanchang, Jinan, Qingdao, Zhengzhou, Wuhan, Changsha, Nanning, Haikou, Chongqing, Chengdu, Kunming, Xi'an, Lanzhou, Urumqi, Guiyang, Yinchuan
Tier 3 cities and Tier 4 Cities (66)	Sanya, Dongguan, Dongying, Zhongshan, Foshan, Baoding, Baotou, Beihai, Nantong, Taizhou, Jilin, Tangshan, Jiaxing, Weihai, Yichang, Baoji, Suqian, Changzhou, Changshu, Langfang, Zhangjiagang, Xuzhou, Dezhou, Huizhou, Yangzhou, Xinxiang, Rizhao, Kunshan, Liuzhou, Zhuzhou, Guilin, Shantou, Jiangmen, Jiangyin, Shaoxing, Mianyang, Liaocheng, Wuhu, Suzhou, Heze, Yingkou, Hengshui, Ganzhou, Lianyungang, Handan, Ordos, Jinhua, Zhenjiang, Ma'anshan, Anshan, Yantai, Zibo, Huai'an, Wenzhou, Huzhou, Xiangtan, Zhanjiang, Weifang, Zhuhai, Yancheng, Qinhuangdao, Luoyang, Tai'an, Xining, Quanzhou, Taizhou

Notes: This table categorizes cities into Tier 1, Tier 2, and Tier 3/4 based on the classification by the National Bureau of Statistics of China. All cities not classified as Tier 1 or Tier 2 are considered Tier 3 cities and Tier 4.

Table 2: Summary statistics: survey sample and random selected sample

Survey sample

	N	Mean	St. Dev	P25	Median	P75
Tier 1&2						
Consumption (RMB)	1,124,570	5,870	17,981	1,252	2,596	5,540
Age	1,124,570	34.735	8.924	28	33	40
Gender (Male=0, Female=1)	1,124,570	0.324	0.480	0	0	1
house prices (RMB)	1,124,570	25,437	15,571	11,976	21,172	42,619
Bank loan to GDP ratio	1,124,570	2.275	0.448	1.990	2.189	2.472
GDP per capita (log)	1,124,570	11.727	0.303	11.526	11.820	11.940
Tier 3&4						
Consumption (RMB)	651,449	6,016	25,887	1,127	2,376	5,152
Age	651,449	34.495	8.203	28	33	39
Gender (Male=0, Female=1)	651,449	0.287	0.452	0	0	1
house prices (RMB)	651,449	12,070	4,128	8,802	11,363	15,533
Bank loan to GDP ratio	651,449	1.356	0.399	1.041	1.339	1.651
GDP per capita (log)	651,449	11.501	0.406	11.232	11.553	11.814

Random selected sample

	N	Mean	St. Dev	P25	Median	P75
Tier 1&2						
Consumption (RMB)	2,380,540	6,931	35,025	1,369	2,879	6,254
Age	2,380,540	30.950	8.685	24	29	35
Gender (Male=0, Female=1)	2,380,540	0.570	0.495	0	1	1
house prices (RMB)	2,380,540	25,263	15,906	11,790	18,954	42,804
Bank loan to GDP ratio	2,380,540	2.256	0.452	1.980	2.175	2.400
GDP per capita (log)	2,380,540	11.704	0.311	11.487	11.802	11.936
Tier 3&4						
Consumption (RMB)	1,197,150	7,732	60,689	1,267	2,734	6,119
Age	1,197,150	31.157	8.173	25	30	36
Gender (Male=0, Female=1)	1,197,150	0.552	0.497	0	1	1
house prices (RMB)	1,197,150	12,130	4,210	8,731	11,146	15,550
Bank loan to GDP ratio	1,197,150	1.365	0.414	1.040	1.339	1.689
GDP per capita (log)	1,197,150	11.498	0.403	11.220	11.551	11.814

Notes: The sample period is from January 2017 to March 2023 and the sample includes 33 Tier 1&2 cities and 66 Tier 3 cities and Tier 4 cities. Housing price is at the city-month level. Bank loan to GDP 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 3: First Stage Regression

Variable	House price
Lagged house price	0.591***
	(0.000)
Bank loan to GDP ratio	0.051***
	(0.000)
GDP per capita (log)	0.086***
	(0.000)
Lagged Fiscal Revenues (log)	0.327***
	(0.001)
Lagged Fiscal Revenues (log) × Mortgage Rate	-0.034**
	(0.000)
Observation	1776019
R^2	0.0056

Notes: The table shows the first stage regression results. The sample period is from January 2017 to March 2023 and the sample includes 33 Tier 1&2 cities and 66 Tier 3&4 cities. The unit of observation is user-month. All variables labeled as "Lagged" are lagged by one year. Standard errors are shown in parentheses. *, **, and *** represent results significant at the 10%, 5%, and 1% levels, respectively.

Table 4: Baseline using IVs

	Consumption			
	Tier 1&2	Tier 1&2	Tier 3&4	Tier 3&4
House price (IV)	0.193***	0.161***	-0.049	-0.043
	(0.050)	(0.060)	(0.055)	(0.055)
Bank loan to GDP ratio		0.042		-0.020
		(0.034)		(0.033)
GDP per capita (log)		0.053		-0.446***
		(0.078)		(0.061)
Observation	1124570	1124570	651449	651449
R^2	0.002	0.006	0.002	0.021
F-statistic (robust)	15.171	5.817	1.876	19.900
User fixed effects	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes

Notes: The sample period is from January 2017 to March 2023 and the sample includes 33 Tier 1&2 cities and 66 Tier 3&4 cities. The unit of observation is user-month. Housing price is instrumented. Bank loan to GDP 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. The R^2 reported is the within R^2. *, **, 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: 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)	0.063	0.208***	0.285***	-0.202***	-0.058	0.224**
	(0.067)	(0.079)	(0.084)	(0.077)	(0.070)	(0.089)
Bank loan to GDP ratio	0.113***	0.012	-0.111**	0.018	0.106**	-0.334***
	(0.037)	(0.045)	(0.050)	(0.051)	(0.047)	(0.061)
GDP per capita (log)	0.206**	-0.113	-0.062	-0.446***	-0.283***	-0.765***
	(0.088)	(0.107)	(0.105)	(0.091)	(0.084)	(0.113)
Observation	402262	470867	251421	225830	285354	140257
R^2	0.015	0.001	0.006	0.027	0.006	0.045
F-statistic	5.792	4.441	3.851	13.019	7.836	20.278
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 2017 to March 2023 and the sample includes 33 tier 1&2 cities and 66 Tier 3 cities and Tier 4 cities. The unit of observation is user-month. Housing price is instrumented. Bank loan to GDP 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. The R^2 reported is the within R^2, which measures the explanatory power of the model for variations within individual units over time. The F-statistic is reported for the joint significance of the instruments in the first stage regression. *, **, 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: Baseline weighted according to the national age and gender distribution

	Consumption			
	Tier 1&2	Tier 1&2	Tier 3&4	Tier 3&4
House price (IV)	0.242***	0.183***	-0.039	-0.034
	(0.039)	(0.060)	(0.057)	(0.057)
Bank loan to GDP ratio		0.030		-0.022
		(0.035)		(0.033)
GDP per capita (log)		0.048		-0.472***
		(0.078)		(0.063)
Observation	1124550	1124550	651428	651428
R^2	0.004	0.005	0.001	0.021
F-statistic (robust)	16.431	5.799	0.464	20.463
User fixed effects	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes

Notes: The sample period is from January 2017 to March 2023 and the sample includes 33 Tier 1&2 cities and 66 Tier 3&4 cities. The unit of observation is user-month. Housing price is instrumented. Bank loan to GDP 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. The R^2 reported is the within R^2. *, **, 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: Home owner vs renter

	Tier 1&2		Tier 3&4	
	Renter	Owner	Renter	Owner
All instrument variables				
House price (IV)	0.012	0.206***	-0.146	-0.029
	(0.081)	(0.063)	(0.103)	(0.059)
Bank loan to GDP ratio	0.066	0.031	0.0004	-0.031
	(0.051)	(0.036)	(0.060)	(0.036)
GDP per capita (log)	-0.021	0.059	-0.458***	-0.441***
	(0.124)	(0.079)	(0.126)	(0.067)
Observation	185274	939960	98271	553763
R^2	0.004	0.005	0.026	0.020
F-statistic (robust)	1.294	7.051	5.821	15.684
User fixed effects	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes

Notes: The sample period is from January 2017 to March 2023 and the sample includes 33 Tier 1&2 cities and 66 Tier 3 cities and Tier 4 cities. The unit of observation is user-month. Housing price is instrumented at the city-month level. Bank loan to GDP 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. The R^2 reported is the within R^2, which measures the explanatory power of the model for variations within individual units over time. The F-statistic is reported for the joint significance of the instruments in the first stage regression. *, **, 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 8: Baseline using random sample

	Consumption			
	Tier 1&2	Tier 1&2	Tier 3&4	Tier 3&4
House price (IV)	0.295***	0.263**	0.215	0.205
	(0.115)	(0.125)	(0.152)	(0.157)
Bank loan to GDP ratio		0.025		-0.021
		(0.085)		(0.066)
GDP per capita (log)		-0.029		-0.223
		(0.241)		(0.143)
Observation	2380540	2380540	1197150	1197150
R^2	0.013	0.005	0.012	0.002
F-statistic (robust)	6.631	2.417	1.995	1.454
User fixed effects	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes

Notes: The sample period is from January 2017 to March 2023 and the sample includes 33 Tier 1&2 cities and 66 Tier 3&4 cities. The unit of observation is user-month. Housing price is instrumented. Bank loan to GDP 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. The R^2 reported is the within R^2. *, **, 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 9: City-Level Aggregation

	Consumption			
	Tier 1&2	Tier 1&2	Tier 3&4	Tier 3&4
House price (IV)	0.227***	0.309***	-0.176	-0.274
	(0.100)	(0.125)	(0.202)	(0.205)
Bank loan to GDP ratio		-0.130		0.993***
		(0.073)		(0.219)
GDP per capita (log)		-0.472		1.934**
		(0.148)		(0.820)
Observation	1,218	1,218	695	695
R^2	0.038	0.097	0.068	0.498
F-statistic (robust)	5.178	5.690	0.751	10.549
User fixed effects	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes

Notes: The sample period is from January 2017 to March 2023 and the sample includes 33 Tier 1&2 cities and 66 Tier 3 cities and Tier 4 cities. Housing price is at the city-month level. Bank loan to GDP 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 10: Baseline using random sample

	Consumption share: offline vs. online			
	Tier 1&2	Tier 1&2	Tier 3&4	Tier 3&4
House price (IV)	0.063***	0.075***	0.004	0.007
	(0.147)	(0.015)	(0.012)	(0.012)
Bank loan to GDP ratio		-0.027***		-0.014**
		(0.007)		(0.006)
GDP per capita (log)		-0.076***		-0.124***
		(0.017)		(0.013)
Observation	1124571	1124571	651475	651475
R^2	0.002	0.015	0.0002	0.023
F-statistic (robust)	18.177	19.050	0.102	29.973
User fixed effects	Yes	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes	Yes

Notes: The sample period is from January 2017 to March 2023 and the sample includes 33 Tier 1&2 cities and 66 Tier 3&4 cities. The unit of observation is user-month. Housing price is instrumented. Bank loan to GDP 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. The R^2 reported is the within R^2. *, **, 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.

Previous volumes in this series

1318 December 2025	Auction-based liquidity saving mechanisms	Rodney Garratt, Morten Bech, Marko Nanut Petric and Caner Ates
1317 December 2025	From listings to all-tenant rents: a probabilistic model	Emanuel Nussli, Rachel Arulraj-Cordonier, Flurina Strasser, Marko Nanut Petrič, Morten Bech and Antonio Pipino
1316 December 2025	Assessing the macroeconomic impacts of the 2025 US tariffs	Hongyan Zhao
1315 December 2025	The ripple effect: supply chain reconfigurations and cross-border credit dynamics	Ricardo Correa, Andrea Fabiani, Matias Ossandon Busch and Miguel Sarmiento
1314 December 2025	The economics of water scarcity	Jon Frost, Carlos Madeira and Serafín Martínez Jaramillo
1313 December 2025	Macroeconomic effects of carbon-intensive energy price changes: a model comparison	Matthias Burgert, Matthieu Darracq Pariès, Luigi Durand, Mario González, Romanos Priftis, Oke Röhe, Matthias Rottner, Edgar Silgado-Gómez, Nikolai Stähler and Janos Varga
1312 December 2025	Generative economic modeling	Hanno Kase, Fabio Stohler and Matthias Rottner
1311 November 2025	When bricks meet bytes: does tokenisation fill gaps in traditional real estate markets?	Giulio Cornelli
1310 November 2025	AI agents for cash management in payment systems	Iñaki Aldasoro and Ajit Desai
1309 November 2025	Making suptech work: evidence on the key drivers of adoption	Leonardo Gambacorta, Nico Lauridsen, Samir Kiuhan-Vásquez and Jermy Prenio
1308 November 2025	Environmental factors and capital flows to emerging markets	Jose Aurazo, Rafael Guerra, Pablo Tomasini, Alexandre Tombini and Christian Upper
1307 November 2025	When is less more? Bank arrangements for liquidity vs central bank support	Viral V Acharya, Raghuram Rajan and Zhi Quan (Bill) Shu