Mortgage Prepayments in China and Monetary Policy Transmission*

Zhenyu Gao, Wenxi Jiang, Haohan Ren, Kemin Wang, Yuezhi Wu

January 15, 2025

Abstract

Despite restrictions on mortgage refinancing, Chinese households prepaid an unprecedented amount of mortgage loans between 2021 and 2024, when the government cut interest rates to combat economic slowdown. Using loan-level data from a large commercial bank in China, we find that households are likely to prepay when the gap between their own mortgage rate and the benchmark rate becomes positive and increases. Evidence further suggests that households prepay with their savings (rather than through refinancing), and the prepayment is associated with household deleveraging and consumption reduction. Combining this with the data of UnionPay card spending, we find macro-level evidence that as the national lending rate decreases, cities with more mortgage borrowers having a positive rate gap tend to experience greater prepayment and consumption reduction. Our findings suggest that frictions in the mortgage market could significantly weaken the transmission of monetary policy.

*We thank Kaiji Chen, Hanming Fang, Jungsuk Han, Chao He, Zhiguo He, Liang Jiang, Ron Kaniel, John Kuong, Chang Ma, Jun Pan, Shang-Jin Wei, Wenbin Wu, Liyan Yang, and seminar participants at CUHK, Fudan University, 2nd HKU Summer Finance Workshop, NBER Chinese Economy Working Group Meeting (Fall 2024), and SFS Cavalcade Asia-Pacific 2024 for helpful comments. Zhenyu Gao and Wenxi Jiang are at the Department of Finance, CUHK Business School, The Chinese University of Hong Kong, Shatin, Hong Kong; and Haohan Ren, Kemin Wang, and Yuezhi Wu are at the Department of Finance, School of Management, Fudan University, Shanghai, China. Authors' contact information: Gao: gaozhenyu@baf.cuhk.edu.hk; Jiang: wenxijiang@baf.cuhk.edu.hk; Ren: haohanren@fudan.edu.cn; Wang: wangkm@fudan.edu.cn; and Wu: wuyz23@m.fudan.edu.cn. Funding: This work was supported by the National Natural Science Foundation of China (Grants 72432001 and 72372029).

1. Introduction

In response to the economic slowdown, China's central bank began cutting interest rates in 2021 to boost lending and revive the real estate market. However, an unintended consequence emerged: Chinese households rushed to prepay their mortgage loans. Unlike in other countries, mortgage refinancing is prohibited in China. Anecdotal evidence suggests that prepayments were financed by household savings , indicating household deleveraging—contrary to the intended goal of expansionary monetary policy.[1] Market observers estimated that total mortgage prepayments in 2022 amounted to 4.7 trillion RMB (700 billion USD), or 12% of China's total outstanding mortgage loans.[2] This trend persisted into the first half of 2023: based on loan-level data from a leading commercial bank, the ratio of mortgage prepayments to newly issued mortgage loans rose to 86%.

The unprecedented wave of mortgage prepayments in China raised concerns not only for commercial banks, which faced profitability challenges, but also for the central bank, as it disrupted the transmission of monetary policy. Between 2021 and 2024, in an effort to counter the economic downturn, the People's Bank of China (PBC) repeatedly injected liquidity and reduced borrowing costs. The 5-year Loan Prime Rate (LPR)—the reference rate for loans—was lowered from 4.85% in October 2019 to 3.95% by May 2024.

However, Chinese households derive limited benefits from reduced borrowing costs due to frictions in the mortgage market. First, the interest rates on existing mortgages are only partially adjusted to the new benchmark rate, and often with a delay. In China, mortgage rates are determined as LPR plus a locally set margin. This local margin, established at the time of mortgage issuance, is a fixed component based on city-level home purchase policies, whereas the LPR is a floating component that is typically adjusted only on an annual basis. Consequently, under current conditions, the rates on many existing mortgage loans have become significantly higher than the prevailing benchmark rate. Second, there is no formal refinancing mechanism in the market that allows households to refinance their

[1] Cao, "Chinese Consumers' Lack of Confidence Is Causing a Rush of Mortgage Prepayments," Wall Street Journal, April 2023.

[2] Liu and Zhang, "Five Things to Know About Early Mortgage Repayments in China," Caixin Global, April 2023. According to the quarterly report from the People's Bank of China (PBC), outstanding mortgage loans stood at 38.8 trillion RMB at the end of 2022; see https://www.gov.cn/xinwen/2023-02/03/content_5739947.htm.

mortgage loans. More specifically, mortgage refinancing is strictly prohibited by regulation in China. These two frictions—stemming largely from the market power of state-owned banks—undermine the effectiveness of monetary policy transmission through the household debt channel.

On the asset side of household balance sheets, returns on bank deposits and wealth management products (WMPs) are adjusted immediately in response to changes in the benchmark interest rate. These adjustments tend to be amplified, with a beta greater than one. For example, between 2019 and 2023, the Loan Prime Rate (LPR) decreased by 60 basis points, while the average return on WMPs dropped by 72 to 95 basis points. Surveys reveal that over 60% of Chinese households' financial assets are allocated to bank deposits and WMPs.[3] Consequently, the gap between financing costs (mortgage rates) and returns on savings has widened significantly as the LPR has declined. This growing rate gap incentivizes borrowers to prepay their mortgages using their savings, as holding savings becomes increasingly expensive by comparison. Moreover, some households may even reduce their consumption to allocate more income toward mortgage prepayment, aiming to lower their interest expenses.

Such mechanism of mortgage prepayment in China make it distinct from the case in developed markets. In those economies, mortgage prepayments are typically refinanced with new loans, and prepaying households tend to be financially constrained (e.g., Berger, Milbradt, Tourre, and Vavra 2021; Eichenbaum, Rebelo, and Wong 2022). More importantly, the implications for monetary policy transmission differ significantly: after rate cuts, Chinese households repay loans using their savings, resulting in deleveraging and reduced consumption. In contrast, US borrowers refinance, enabling increased borrowing and higher consumption. This mechanism in China underscores the critical role of frictions and market power in the banking sector in shaping the effectiveness of monetary policies. In response to this challenge, in September 2024, PBC implemented unconventional measures—a universal reduction in mortgage rates nationwide—to address these obstacles and stimulate household consumption.

With using granular loan-level data, our study is the first to investigate the motives

[3] https://www.htsec.com/jfimg/colimg/upload/20200511/99691589164486214.pdf

driving household mortgage prepayments and their implications for monetary policy transmission. Furthermore, we assess the effectiveness of unconventional monetary measures through an analysis of a pilot policy program. Our findings provide valuable insights into how frictions in the banking sector can obstruct the transmission of monetary policy via the mortgage market channel.

The loan-level data is provided by one of the nationwide banks in China from October 2019 to May 2024. This bank has branches all over the country with a large share of the mortgage market. We randomly select 100,000 mortgage loans at the beginning of the sample period for our loan-level analysis. 37.5% of the borrowers have made at least one prepayment during the sample period. The majority of prepayments are partial: the average prepayment amount equals 170,460 yuan, whereas the mortgage balance at the time of prepayment is 426,357 yuan. This is consistent with the observation that Chinese households are using their savings to prepay mortgages rather than refinancing them.

We begin by examining the motives behind mortgage prepayments. Chinese households often maintain savings while carrying mortgage debt, with investing these savings into WMPs. Despite the fact that the average return on WMPs is typically lower than the mortgage rate, households often view this gap as a premium they pay for maintaining precautionary liquidity. However, this optimal choice may shift when the central bank makes significant cuts to benchmark interest rates. The core mechanism lies in the asymmetric transmission of the interest rate channel between the two sides of households' balance sheets. On the financing side, mortgage loan rates are rigid, adjusting only partially to reductions in LPR and with a delay. On the asset side, returns on WMPs adjust quickly to the benchmark rate, often with amplification. Therefore, as the LPR decreases, the gap between households' investment returns and financing costs widens significantly, incentivizing households to reduce their borrowing by prepaying their mortgages.

To test this conjecture, we calculate interest rate gap as a household's current mortgage rate minus LPR, denoted as *RateGap*. We use LPR as our primary proxy for households' returns (our results are robust using other proxies, such as average returns of WMPs). We first regress a prepay dummy over the next six months at the loan level onto interest rate gap (denoted as *RateGap*), which equals the borrower's current mortgage rate minus LPR. We hypothesize that borrowers are more likely to prepay when *RateGap* increases. Importantly, we control for year-month fixed effects to rule out the potential macroeconomic confounding effects. For example, it could be the case that both the central bank and households expect an economic downturn in the future, then the central bank cuts the rate and households decide to reduce borrowing by prepaying. Our identification tries to separate such effect by exploiting the cross-sectional variations in the fixed component (that is, local margin) of the mortgage rate. The local margin depends on factors at mortgage issuance, such as local cities' mortgage policies and borrowers' home portfolio.[4] Our assumption is that the variation in the fixed component is orthogonal to households' current expectation of future economy.

We find that households are more likely to prepay as the rate gap between their current mortgage interest and LPR increases. As the rate gap increases by 50 basis points, the likelihood to prepay mortgage over the next six months rises by 0.77%, which is economically meaningful given that the average likelihood of prepay in 6 months is 6.3% over the sample period. This finding is robust to controlling for household characteristics and local economic conditions including GDP growth, housing price, and inflation.

An important prediction of our hypothesis is the presence of an asymmetric effect: households are more likely to prepay their mortgages only when the *RateGap* becomes sufficiently large, while we expect an insignificant effect when the *RateGap* is negative. Although it is unclear where the precise threshold (or "kink") lies, we allow the data to guide us. We experiment with a wide range of breakpoints and various proxies for household savings returns, such as the average returns of different types of WMPs and LPR. Across all specifications, we consistently uncover a robust, non-linear relationship between *RateGap* and prepayment behavior; see Figure 2. The specification that best fits the data, as determined by R^2, uses the LPR as the proxy for savings returns and sets the breakpoint at zero. Based on this finding, we adopt this as our primary specification for the remainder of the analysis.

This non-linear pattern bears some resemblance to findings in the U.S. mortgage market. For instance, Berger et al. (2021) show that the gap between existing and new mortgage rates can trigger significant prepayment activity, with the effect exhibiting a step-like func-

[4] See more details in Section 2.

tion around zero. However, we argue that the patterns observed in China differ in several important ways due to distinct underlying mechanisms.

First, in China, the propensity for prepayment continues to increase as the *RateGap* grows larger, whereas in the U.S., the effect is concentrated just above zero, resembling a step-like function. Second, a key condition for our hypothesis is that households must have sufficient savings to make prepayments, as mortgage refinancing is not allowed in China. This implies that the effect should be stronger for more affluent borrowers. Indeed, our results confirm that households with greater liquid investments, higher levels of education, and better credit scores are more responsive to increases in the *RateGap* and more likely to prepay their mortgages. By contrast, evidence from the U.S. shows that it is predominantly low-income households that engage in prepayment, driven by financial constraints and a stronger desire to reduce interest expenses. Third, consistent with our hypothesis, prepaying households in China experience a substantial and sustained decline in their long-term savings levels, which decrease by approximately 72 to 78% following prepayment. This contrasts with the U.S., where prepayment behavior is often associated with refinancing rather than drawing down savings, leading to different implications for household balance sheets and consumption behaviors.

We next examine households' consumption patterns before and after mortgage prepayment. To formalize the intuition, we develop a stylized model in Appendix C that illustrates a household's consumption and prepayment decisions. The model demonstrates that, under certain conditions, Chinese households may reduce their short-term consumption after prepaying their mortgages. This behavior reflects their desire to accelerate mortgage prepayment and avoid future interest expenses, especially as the *RateGap* becomes substantially large. Using bank card transaction data (including both credit and debit card activity), we find consistent empirical evidence: households that prepaid their mortgages tend to reduce their consumption by approximately 5% afterward. This finding highlights a potentially counterproductive effect of monetary policy, at least through the mortgage prepayment channel: cutting benchmark rates without adjusting mortgage interest rates accordingly could inadvertently lead to a reduction in household consumption.

This pattern again stands in contrast to evidence from the U.S., where cutting interest rates typically facilitates mortgage prepayment or refinancing. In the U.S., refinancing often results in increased leverage and reduced household interest expenses, which subsequently boosts consumption. In China, however, the absence of refinancing options forces households to use their savings for prepayment, leading to a decline in available liquidity for consumption. This underscores the distinct mechanisms at play in the two countries' mortgage markets and their implications for monetary policy transmission.

We further exploit a policy experiment implemented by regulators to provide supportive evidence for our hypothesis. On August 31, 2023, the PBC announced a one-time reduction in the local margin (i.e., the fixed component of mortgage rate) of eligible households' mortgage rates. Eligible households were defined as those whose mortgage loans were for a second home. Approximately one-quarter of the households in our sample qualified for this policy, with their mortgage rates—and consequently their *RateGap*—reduced by an average of 50 basis points. Using a difference-in-difference framework, we find that treated households were less likely to prepay their mortgages after the policy change and tend to increase consumption relative to the control group. These results provide strong evidence that reducing the *RateGap* can mitigate the incentive for mortgage prepayments and stimulate household consumption.

In the second part of the paper, we analyze the implications of mortgage prepayment behavior for monetary policy transmission. At the household level, we find that the rigidity of mortgage rates causes households to deleverage and reduce consumption as PBC cuts interest rates. We then extend our analysis to examine the macroeconomic consequences of this behavior, focusing on aggregate consumption at the city level. A key challenge in this analysis is identifying the causal effect of interest rate cuts on household consumption through the mortgage prepayment channel. Various confounding factors could potentially drive the observed correlation between monetary policy, mortgage prepayment, and consumption reduction. For instance, pessimistic expectations about the economy or real estate prices may simultaneously influence central bank rate cuts and household decisions on prepayment and consumption. While this expectation channel is compelling, it is not exclusive to the repayment channel we focus on. Our objective is to isolate and identify the causal effect of LPR adjustments on household consumption.

To address this challenge, we exploit cross-regional variation in $Frac > 0$, the fraction of borrowers in a city whose mortgage rates exceed the current LPR. While the adjustment of LPR is uniform across the nation, its induced policy impact on mortgage prepayment varies substantially across cities. This variation depends on the city's average mortgage loan rates, which are path-dependent and influenced by local factors such as the timing of mortgage issuances and local margin policies in effect at the time. Since the fixed component of existing mortgage rates (the local margin) is determined at issuance, it is plausibly orthogonal to households' current expectations about the local economy. Additionally, by using $Frac > 0$ instead of the city-level average *RateGap*, we exploit the "kink" in the relationship between *RateGap* and prepayment decisions, which strengthens the identification power of our tests.

Specifically, we aggregate individual prepayment behavior by city and calculate *PrepayCount*, the fraction of mortgage borrowers in a city who prepay during months $t+1$ to $t+6$. We then use $Frac > 0$ at the city level as an instrumental variable (IV) for *PrepayCount*. In the second-stage regression, we use the instrumented *PrepayCount* to predict subsequent growth in total consumption. To measure city-level aggregate consumption, we rely on total spending through UnionPay bank cards.[5] Our approach allows us to plausibly disentangle the causal impact of rate cuts on household consumption via the mortgage prepayment channel.

Our IV regression results find a significantly negative correlation between *PrepayCount* and the subsequent consumption growth. The economic magnitude is also meaningful: a one-standard-deviation increase in the fraction of prepayments is associated with a 19.6% decrease in aggregate consumption. Moreover, such an effect is more pronounced for discretionary spending.

Finally, we discuss the policy implications based on our findings. First, one can think of $Frac > 0$ as a predictor of monetary policies' effectiveness. That is, we show that in the cities where more borrowers paying mortgage rates higher than LPR, reductions in LPR are likely to be counterproductive in boosting household borrowing and consumption. Second, our findings point out that the frictions in the mortgage, such as delayed adjust-

[5] The data includes transactions made directly via bank cards through POS systems and digital wallets such as Alipay and WeChat Pay, provided the bank cards are linked to the wallets.

ment to benchmark rate and the lack of mortgage refinancing, that prevent monetary policy from passing to the households' borrowing cost could significantly weaken or even generate counter-productive effect on monetary policy transmission. Our event study based on the policy shock suggests that in such market environment, unconventional measures of monetary policy may be necessary and useful. Agarwal, Deng, Gu, He, Qian, and Ren (2022) find that in 2008 as the Chinese regulator cut the benchmark lending rate and applied the new rate immediately to all existing mortgages, which led to increases in household consumption. All the evidence justifies the most recent policy changes by the PBC, that is to reduce the mortgage rate (through changing local margin) of all mortgage loans national wide by 50 basis points on average. To make it more formal, it is crucial to allow household mortgage rates to perfectly float with the central bank's benchmark rate to make the monetary policy transmission effective.

Our IV regression results reveal a significantly negative correlation between $PrepayCount$ and subsequent consumption growth. The economic magnitude of this relationship is substantial: a one-standard-deviation increase in the fraction of prepayments is associated with a 19.6% decrease in aggregate consumption. Moreover, this effect is particularly pronounced for discretionary spending.

Finally, we discuss the policy implications of our findings. First, $Frac > 0$ can serve as a useful predictor of the effectiveness of monetary policy. Specifically, we show that in cities where a larger proportion of borrowers are paying mortgage rates above the current LPR, reductions in LPR are less likely—or even counterproductive—in stimulating household borrowing and consumption. Second, our results highlight the critical role of frictions in the mortgage market, such as the delayed adjustment of mortgage rates to the benchmark rate and the absence of mortgage refinancing options. These frictions significantly hinder the transmission of monetary policy to households' borrowing costs, which, in turn, weakens or even reverses the intended effects of monetary easing. Our event study, based on the policy shock, suggests that in such a constrained market environment, unconventional monetary measures may be both necessary and effective.[6] Our finding supports the most recent policy

[6] Our results also echoes Agarwal et al. (2022), who document that during the 2008 financial crisis, the Chinese regulator implemented a policy mandating that reductions in the benchmark lending rate immediately apply to all existing mortgages, and it led to measurable increases in household consumption.

action by the PBC in October 2024 to reduce the mortgage rate (via adjustments to the local margin) for all mortgage loans nationwide by an average of 50 basis points.[7] Utimately, it is crucial to allow household mortgage rates to fully float with the central bank's benchmark rate. Such a reform would enhance the effectiveness of monetary policy transmission by ensuring that reductions in benchmark rates directly lower households' borrowing costs, thereby boosting consumption and achieving the desired macroeconomic outcomes.

Literature Review Our paper is related to the literature on several fronts. First, our paper contributes to the literature on the effect of interest rate changes on mortgage prepayment and refinancing (e.g., Dunn and McConnell (1981), Green and Shoven (1986), Schwartz and Torous (1989), and Deng, Quigley, and Van Order (2000)). More recently, scholars have explored the heterogeneity in responses to interest rate changes and the obstacles faced in making prepayment decisions, such as financial frictions and inattention (Agarwal, Rosen, and Yao (2016); Bhutta and Keys (2016); Keys, Pope, and Pope (2016); Andersen, Campbell, Nielsen, and Ramadorai (2020)). Our paper is primarily connected to two studies that investigate the distribution of mortgage rates to generate state-dependent prepayment decisions (Berger et al. (2021); Eichenbaum et al. (2022)). However, the lack of refinancing options in China introduces a distinctive element, which alters the consequences of prepayment and affects the effectiveness of monetary policy in this context.

Previous research on mortgage prepayment has predominantly focused on the US market. However, scholars such as Badarinza, Campbell, and Ramadorai (2016) have emphasized the importance of adopting an international comparative approach to studying household finance. While there are a few exceptions, such as Miles (2004) examining the UK, Bajo and Barbi (2018) investigating Italy, and Andersen et al. (2020) exploring Denmark, the literature on mortgage prepayment in non-US markets remains relatively limited and has little coverage on emerging markets. In line with findings from other markets, our study reveals that reductions in interest rates serve as an incentive for households in China to engage in mortgage prepayment. However, a distinctive characteristic of an emerging market like China is market frictions such as the lack of refinancing options. Consequently, prepayment in response to rate cuts in China leads to a reduction rather than an increase in

[7] http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/5471189/index.html

household borrowing and consumption, highlighting an unintended consequence of mortgage prepayment.

Second, we contribute to the literature on the role of mortgages in the transmission of monetary policy (e.g., Iacoviello (2005), Rubio (2011), Garriga, Kydland, and Šustek (2017), Greenwald (2018), and Drechsler, Savov, Schnabl, and Supera (2024)). Recent studies, utilizing more detailed cross-sectional data, such as Agarwal, Green, Rosenblatt, and Yao (2015), Di Maggio, Kermani, and Palmer (2016), Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao (2017), Auclert (2019), Beraja, Fuster, Hurst, and Vavra (2019), and Cloyne, Ferreira, and Surico (2020), have explored the heterogeneity effect of monetary policy transmission through mortgage markets. While our study also confirms that households' decision to prepay their mortgages is influenced by the historical pattern of interest rates and the distribution of mortgage rates and is thus path- and state-dependent, as noted by Berger et al. (2021) and Eichenbaum et al. (2022), the outcome of monetary policy through the prepayment channel in China diverges entirely from the findings documented in the literature for the US. Specifically, households in China reduce their borrowing and consumption rather than increase them after mortgage prepayment induced by interest rate cuts.

Third, our paper is related to the literature on bank market power and monetary policy transmission. Drechsler, Savov, and Schnabl (2018) illustrate that deposit rates do not rise significantly after monetary tightening due to banks' market power. Scharfstein and Sunderam (2016) note that mortgage rates fall less in response to monetary easing in concentrated markets. Wang, Whited, Wu and Xiao (2022) quantify these effects through a structural model, while Kacperczyk and Schnabl (2013) and La Spada (2018) discuss the behavior of money market funds during times of monetary easing, highlighting risk-seeking behaviors in low-rate environments. Our analysis involves the heterogeneous rate pass-through across household balance sheets and emphasizes that the aggregated effects of monetary easing can lead to counter-productive outcomes for households, particularly as active prepaying households—often wealthier and more educated—drive these dynamics.

Fourth, our paper makes a substantial contribution to the extensive literature on household borrowing and consumption, with a particular focus on the relationship between consumption, household leverage, and savings. Notable studies, such as Mian, Rao, and Sufi

(2013) and Chen, Michaux, and Roussanov (2020a), investigate the influence of household debt and housing-related assets on consumer spending during the housing boom. In our study, we empirically document a compelling deleveraging effect on household consumption through their savings during the economic downturn. We therefore also contribute to the empirical literature on savings and consumption such as Caballero (1990), Gourinchas and Parker (2001), Parker and Preston (2005), and Christelis, Georgarakos, Jappelli, and Van Rooij (2020).

Lastly, our study makes a valuable contribution to the literature on understanding monetary policy in China. China's monetary policy exerts a significant influence on both the domestic economy and global financial markets, yet it remains an area that is not thoroughly comprehended (Huang, Ge, and Chu (2019)). An emerging body of literature, including works by Chen, Ren, and Zha (2018), Chen, He, and Liu (2020b) and Chen, Gao, Higgins, Waggoner, and Zha (2023b), has examined monetary stimulus with a specific focus on the banking system, particularly the rise of shadow banking in China. In our paper, we shift the focus to the transmission of monetary policy through the housing market in China. Real estate holds substantial importance not only in the country's economy but also as a vital component of its financial system (Liu and Xiong, 2023; Xiong (2023)). Surprisingly, the mortgage channel of monetary policy transmission in the Chinese context has received limited attention, despite the significant role played by real estate markets in driving China's economic growth. One exception is the study by Agarwal et al. (2022), which examines how "wealthy hand-to-mouth" consumers increase their credit card spending in response to a decrease in their mortgage interest expenses due to interest rate cuts. This finding aligns with existing studies conducted in the United States and other developed countries (e.g., Kaplan and Violante (2014); Kaplan, Violante, and Weidner (2014)). In contrast, our paper focuses on the prepayment channel and uncovers a novel phenomenon, to the best of our knowledge, in the literature. We find that households who engage in early mortgage prepayment due to interest rate cuts for the newly issued mortgages experience a decrease in their consumption, shedding light on a previously undocumented aspect of the relationship between mortgage prepayment and consumption behavior.

2. Institutional Background and Hypothesis

In this section, we introduce institutional details about the Chinese mortgage market. Specifically, we focus on the rules regarding how mortgage rates are determined and adjusted, procedures of mortgage prepayments, and the restrictions on mortgage refinancing. Then, we develop our hypothesis.

2.1. Interest Rate of Mortgage Loans

The BLIR-Based Mortgage Rates Before October 8, 2019, the People's Bank of China (PBC) used the RMB Benchmark Loan Interest Rates for Financial Institutions (BLIR) as the reference rate for loans to individuals and corporations issued by financial institutions (e.g., commercial banks). During this period, the mortgage rates were calculated as the product of BLIR times a local multiplier of the city. For example, the mortgage rate in Beijing in June 2018 was "110% of the benchmark rate," where 110% is the local multiplier. The local multiplier is at the discretion of the prefecture-level cities and may change over time, as it is used as a tool to control local home prices and demand. For example, the Beijing government increased the local multiplier from 85% in October 2016 to 110% in June 2017 to cool down the real estate market.

The benchmark rate, BLIR, is often adjusted by PBC as a tool of the central bank's monetary policy. The adjustments to BLIR were applied to both existing and new mortgages. Local governments may also change the local multiplier to control local home prices, but the adjustments to local multipliers are only applied to new mortgages but do not affect the existing mortgages. That is, the local multiplier for a mortgage remains fixed for the life of the mortgage, thus mortgages issued at different time periods in the same city can use different multipliers.

The LPR-Based Mortgage Rates On October 8, 2019, PBC adopted a new reference rate, Loan Prime Rate (LPR), and a new pricing scheme for mortgage loans. LPR refers to the average of lending rates for prime customers submitted by 20 quoting banks and is published by the National Interbank Funding Center (NIFC) on the 20th day of every month.The interest rate of a mortgage issued after October 8, 2019, is calculated as LPR plus a local margin. For instance, the interest rate of a mortgage issued by banks in Beijing on October 10, 2019, was "LPR+55 bps," where the local margin equals 55 bps. Similar to the local multiplier in the BLIR-based system, the local margin is set by the prefecture-level city as a policy tool for real estate price controls. Local margin can depend on whether it is the household's first home and be higher for investment homes. Policy changes on local margin by the local government are only applied to the subsequent new mortgages, not to existing mortgages. Changes to LPR will be immediately applied to new mortgage loans, but for existing loans, the mortgage rate is adjusted to the most recent LPR only at an annual frequency.[8]

Conversion from BLIR- to LPR-based Rate Mortgage loans issued with BLIR-based rates were required to convert to either an LPR-based rate or a fixed rate. For either choice, the conversion formula is designed in such a way that the interest rates do not change right after the conversion. For example, suppose a mortgage with an interest rate of 5.25% in March 2020 and the LPR in December 2019 was 4.85%.[9] If the borrower chooses an LPR-based rate in March 2020, then the interest rate specified in the new contract (effective on January 1, 2021) would be "LPR + (5.25% − 4.85%)," that is, the local margin is set to be 40 bps for the rest life of the loan. If the borrower opts in a fixed rate, then she would pay a fixed rate of 5.25% till maturity. In both cases, the borrower continues to pay the pre-conversion rate of 5.25% immediately following the conversion. This ensures that the differences in interest rates, which are mostly from the differences in local multipliers, among existing mortgages under the old BLIR-based system are inherited by the differences in the local margins under the new LPR-based system. Over 94% existing mortgages chose the LPR-based pricing scheme.

In sum, the mortgage rate in China features both fixed and floating components. Over our sample period from October 2019 to May 2024, the interest rate of mortgage loans

[8] Specifically, the interest rate of an existing mortgage is adjusted once per year based on the latest LPR right before the adjustment date. Borrowers may select either January 1 or the issuance date of the mortgage as the adjustment date. Once chosen, the adjustment date is fixed.

[9] All the conversions are required to use the LPR in December 2019 to determine the new local margin.

(denoted as m) can be written as, for individual i at month t,

$$m_{i,t} = LPR_{t-\tau} + Local\_Margin_{i,0} \tag{1}$$

where $LPR_{t-\tau}$ refers to the most recent LPR related to i's adjustment date, which is floating with the current LPR but with a delay. $Local\_Margin_{i,0}$ is the fixed component and determined at the issuance of the mortgage. The heterogeneity in local margins among households can come from (1) the timing of i's home purchase, (2) whether it is i's first home or not, and (3) the cross-city and time-series variations in policies that determine local margin.

2.2. Mortgage Prepayment and Restrictions on Refinancing

The Chinese regulators do not provide any official channels for mortgage borrowers to refinance their mortgages. Rather, the regulatory rules explicitly prohibit banks or households from issuing new loans to prepay mortgages.[10] While anecdotes suggest that some households may take short-term loans (such as consumer loans) to prepay their mortgages during this episode, such behavior is rare due to the risks and costs. First, taking new loans to prepay mortgages is explicitly prohibited by commercial banks in China; banks can terminate the loan contract if they find it is used for prepaying mortgages. Second, these loans are likely to be short-term, so borrowers must roll over the loans to repay the long-term mortgage, which is costly and can be cut off by the bank. Indeed, according to an internal report of the bank, fewer than 1% of their clients may have used other types of loans to finance mortgage prepayments.

It is very common for households to use their own saving to make mortgage prepayments. However, making mortgage prepayments is subject to some frictions in China. For instance, commercial banks usually only allow a household to have one mortgage prepayment within a calendar year. Also, it may take a few months to finish the whole procedure from application submission to making the final payment. These frictions can have nontrivial impacts on households' saving and consumption behavior. For example, households tend to accumulate more cash right before the once-a-year prepayment.

[10] See https://www.gov.cn/zhengce/zhengceku/2021-03/26/content_5596070.htm.

2.3. *Hypothesis*

In Appendix C, we develop a stylized model to motivate the hypotheses presented in this paper. The key intuition of the model is that mortgage prepayment can be viewed as a form of savings for households, where the "return" on prepayment is the mortgage rate. When the household's savings/investment rate exceeds the mortgage rate, they will choose to save/invest rather than prepay the mortgage. Conversely, when the savings/investment rate is lower than the mortgage rate, prepayment becomes the more optimal choice. Given that mortgage rates can vary across households and time periods when mortgages originated, we expect to observe mortgage prepayment when the gap between a household's current mortgage rate and their savings rate becomes positive. Moreover, the wider this positive gap, the stronger the incentive for households to prepay their mortgages to reduce their financing costs. Our first hypothesis is therefore developed as follows:

Hypothesis 1: Mortgage prepayment has a nonlinear relationship with the gap between the mortgage rate and the household's savings rate. When the gap is negative, households will not choose to prepay. When the gap is positive, prepayment will increase as the gap widens.

Additionally, when interest rates decline, richer households (those with higher income and total assets) who face a positive rate gap between mortgage and savings will have a stronger tendency to prepay their mortgages, as they have more savings and income available to make the prepayments. The model then suggests the second hypothesis:

Hypothesis 2: If the gap between the mortgage rate and savings rate is positive, households with higher income and AUM will prepay their mortgages to a greater extent.

Given the restrictions on mortgage refinancing in China, households are not allowed to obtain new loans to pay off their existing mortgages. As a result, when Chinese households choose to prepay their mortgages, they must utilize their own savings and personal financial resources to do so. This need to tap into their savings accounts or other liquid assets in order to accelerate mortgage payments can lead to a reduction in household deposit balances.

Furthermore, the diversion of funds away from savings and towards mortgage prepayments may also compel some households to cut back on their overall consumption spending. We summarize these mechanisms in Hypothesis 3 as follows:

Hypothesis 3: After the interest rate cuts, in order to prepay their mortgages, households with a positive gap between the mortgage rate and saving rate will deleverage by reducing their deposits and may decrease their consumption.

The predictions about mortgage prepayment behavior in China differ from the dynamics seen in the US market, where mortgage refinancing is a common practice. In the US, when interest rates are cut and new mortgage rates decline, households often choose to refinance their mortgages to secure a lower interest rate. This can be particularly beneficial for households with low incomes or tight financial constraints, as the reduced monthly mortgage payments can free up disposable funds that can then be allocated towards consumption. As a result, US households tend to exhibit a pattern of increased consumption following mortgage prepayment. The lower monthly obligations allow them to devote a greater portion of their disposable income towards discretionary spending.

In contrast, the hypotheses about mortgage prepayment behavior in China do not assume the availability of a mortgage refinancing channel. Consequently, even though both U.S. and Chinese households' prepayment behaviors demonstrate a nonlinear relationship with the gap between the mortgage rate and savings rate, as described in Hypothesis 1, the predictions diverge in other key aspects.

Specifically, the hypothesis for the Chinese market suggests that Chinese households with stronger financial positions are more inclined to prepay their mortgages more aggressively (Hypothesis 2). Furthermore, it is predicted that Chinese households would actually reduce their consumption levels in order to accelerate the prepayment of their mortgages when interest rates decline, rather than increasing consumption (Hypothesis 3).

These distinctions are attributed to the lack of a mortgage refinancing market in China. Without the ability to easily refinance to a lower rate, Chinese households may feel compelled to use savings to pay down their mortgage more quickly, rather than increasing spending, leading to counter-productive monetary polices.

3. Data

3.1. Mortgage Data

Our mortgage data is from one of the largest commercial banks in China. The sample period is from October 2019 to May 2024. We choose October 2019 as the starting point because the LPR-based mortgage rate was implemented in that month.

We first construct a loan-level dataset by randomly selecting 100,000 loans from the population of over 10 million outstanding mortgages as of October 2019. The dataset contains basic information of the mortgage such as a unique ID of the borrower, mortgage location, issuance date, and mortgage maturity; monthly variables including interest rate, remaining mortgage balance, regular monthly payment, the actual payment in a month, and a dummy variable of prepayment; and information about the collateralized real estate property including its purchase price and size. The bank also provides demographic information for the borrower, including age, gender, education level, marriage status, credit score, total deposits, and assets under management (AUM, which includes deposits, wealth management products, and insurance products on the borrower's bank account). The key variable of interest at the loan level is $Prepay_{i,t}$, a dummy variable that equals one if mortgage i is fully or partially prepaid in month t, and zero otherwise. We also calculate $RateGap_{i,t}$ as the difference between an individual's current mortgage interest rate $m_{i,t}$ and LPR_t.

We also construct a city-level dataset, which is compiled from the bank's all outstanding mortgages over our sample period (October 2019 to May 2024) across 267 cities. Specifically, for each city c in a given month t, we compute the ratio of the number of mortgage prepayments to the total number of mortgage payments ($PrepayCount_{c,t}$), the average interest rate of existing mortgages ($M_{c,t}$), the average interest rate of newly-issued mortgages ($LocalNewRate_{c,t}$), and the average house price ($HousingPrice_{c,t}$). We also follow Berger et al. (2021) and compute the fraction of existing mortgages with $RateGap$ greater than zero in a given month ($Frac > 0_{c,t}$).

3.2. Consumption and Macroeconomic Data

We obtain monthly city-level consumption data from UnionPay, which is a state-owned payment card company that manages the largest interbank card transaction settlement network in China. UnionPay was founded through a government initiative to build a unified, effective, and secure bank card network to connect all commercial banks in its association and process interbank settlement and clearing transaction information. As of 2022, UnionPay has more than one billion cardholders and is accepted in 181 countries and regions. A series of papers use the data from UnionPay cards to study household consumption behaviors, e.g., Agarwal, Qian, Seru, and Zhang (2020); Chen, Qian, and Wen (2021); Chen, Qian, and Wen (2023a).

Most interbank card transactions in China are recorded in UnionPay's clearing system. One major category of these transactions is credit/debit card spending through point-of-sale (POS) systems. These spendings include not only transactions conducted directly via bank cards but also those executed through digital wallets such as Alipay and WeChat Pay, provided that consumers use the bank cards linked to their digital wallet accounts to make payments. Each transaction record includes the date, amount in RMB, location, and the merchant's industry classification. The dataset does not contain any information about the cardholders. UnionPay provides us with city-day-level aggregation of individuals' transaction records. We measure the total consumption, discretionary consumption, and essential consumption made through UnionPay bank cards.

We also obtain macroeconomic variables at the city-level and country-level from iFind and CSMAR. These variables include total lending provided by local financial institutions, GDP per capita, GDP growth rate, the Purchasing Managers' Index (PMI), and the Consumer Price Index (CPI).

4. Mortgage Prepayment Behavior: Loan-level Analysis

In this section, we analyze Chinese individuals' mortgage prepayment behavior with the loan-level data. We document the aggregate trend and summary statistics before testing the main hypothesis.

4.1. The Aggregate Trend and Summary Statistics

We start by documenting the aggregate trend of the prepayment waves using our randomly selected sample of 100,000 mortgage loans from the bank. In Figure 1, we plot the level of the 5-year LPR over the sample period (in blue). PBC reduced LPR from 4.85% in September 2019 to 4.65% in April 2020. As the economy further slowed down, PBC started another round of LPR reductions at the end of 2021 and adjusted to 3.95% in May 2024. Along with the LPR rate, we calculate the average ratio of the number of mortgage prepayments to total mortgage repayments, including both regular repayments and prepayments, over the subsequent 6 months. The figure shows that as the PBC started to gradually reduce LPR in 2022, the subsequent prepayments sharply increased and reached the highest 11.5% in 2022.[11] The time-series correlation is consistent with our hypothesis that LPR reductions motivated Chinese households to prepay and deleverage, and we provide further evidence for causal interpretation in the following sections. In terms of headcounts, among our randomly selected sample of 100,000 individuals who have mortgages in October 2019, 37.5% have made at least one full or partial prepayment before May 2024.

[Insert Figure 1 near here]

Panel A of Table 1 presents the summary statistics of the main variables at the loan level. The mean of *Prepay* dummy equals 1.1% per month, which suggests that 13.2% of mortgage borrowers prepay their mortgage per year (remind that one can only prepay once per year). The average *RateGap* is positive 0.34% with the 25th and 75th percentiles of -

[11] The sharp reduction in the prepayment ratio around the second half of 2022 is due to the nationwide COVID-19 lockdown in China at that time.

0.004% and 0.695%, respectively. This means that despite some cross-sectional heterogeneity, the majority of mortgage borrowers are paying higher interest rates than the current LPR. As introduced earlier, this is because the local margin is fixed and there is a delay in adjusting the mortgage rate to the latest LPR. This pattern also reflects the fact that the Chinese economy has been growing fast and it is until recent years that borrowing costs started to decrease.

In Panel B, we compare the characteristics of borrowers who made at least one mortgage prepayment with those who did not prepay at all during the sample period. For the 37.5% who have made at least one prepayment, their average prepayment amount is 170,460 RMB, which constitutes 40% of the mortgage balance of 426,357 RMB at the time of prepayment. This suggests that the majority of prepayments are partial, consistent with the observations that Chinese households are prepaying with their saving rather than refinancing. Also, their prepayment of 170,460 RMB is a significant expenditure compared to their regular repayment of 3,489 RMB.

Mortgage prepayment is a choice, not a randomized treatment; as we discuss in the next subsection, our identification does not rely on a direct comparison between the prepaying and non-prepaying groups. Nonetheless, it is still meaningful to understand their characteristics. The two groups exhibit similar levels of credit score, age, LTV ratio, and home size. *RateGap* at the time of prepayment equals 0.26 for the non-prepaying but is slightly higher 0.33 for the households who prepaid. Prepaying households tend to have more net wealth, better education, more expensive homes, and higher mortgage borrowing and monthly repayments, than non-prepaying ones.

Panel C reports summary statistics of the city-level variables. The average *RateGap_City* is 0.528% with a standard deviation of 0.291% for the city-level sample.

[Insert Table 1 near here]

4.2. Interest Rate Gap and Mortgage Prepayment

4.2.1. Baseline

In the following, we test our main hypothesis that Chinese households tend to prepay their mortgage when their mortgage rate (m) becomes greater than the current interest rate of loans (r, proxied by LPR). As we discussed in Section 2.3, since Chinese households tend to keep precautionary savings, when their saving returns, which are closely linked to r, decrease below m, households will, due to refinancing restrictions, repay mortgages with their savings to lower their interest expenditure.

To test this mechanism, we estimate the following individual-month-level panel regression,

$$Prepay_{i,t+1\to t+6} = \alpha + \beta \cdot RateGap_{i,t} + Controls + \mu_c + \gamma_t + \varepsilon_{i,t} \tag{2}$$

where $Prepay_{i,t+1\to t+6}$ is a dummy variable which equals one if borrower i makes a prepayment between month $t+1$ to month $t+6$, and zero otherwise. We set a 6-month window to identify prepayment behavior because the application for mortgage prepayment typically takes a few months to process and approve (as we discussed in Section 2). We show in Table A2 of the Internet Appendix that our results are robust to alternative prepayment windows. $RateGap_{i,t}$ equals the interest rate of mortgage ($m_{i,t}$) minus the LPR in month t.

Our identification relies on the heterogeneity in each mortgage's fixed component, $Local\_Margin_{i,0}$. Local margin is determined at the time when the mortgage was issued and depending on the local policy and borrowers' home portfolio. Further, we control for year-month (γ_t) and city (μ_c) fixed effects. This is to rule out any possible effects at the city and/or year-month level that can be correlated with $RateGap$ and households' prepayment decisions. For example, it could be an expectation channel driving the observed effects. That is, both PBC and households are pessimistic about the future economy, thus PBC reduced LPR, and households prepaid mortgage to cut borrowing. While this channel is compiling, it is ruled out by the time-fixed effects. In short, the assumption of our identification strategy is that the local margin at issuance is not correlated with the borrower's current expectation of the economy.

We follow Berger et al. (2021) and control for the borrower's gender, education status, age, credit score, total assets in the bank, the quadratic term of the loan-to-value ratio, the remaining mortgage balance, and indicators for mortgage age in month t. We also include a set of macroeconomic variables such as the average housing price in borrower i's city, the growth rate of housing prices, and the lagged housing prices. Standard errors are clustered by year-month.

[Insert Table 2 near here]

Panel A of Table 2 presents the results. In Columns (1) and (2), we include city fixed effects and year-month fixed effects. In Column (3), we add city times year-month fixed effects, which rule out any city-time level economic conditions or factors that could impact prepayment behavior. We do not include borrower fixed effects because our identification relies on the heterogeneity in each borrower's fixed local margin ($Local\_Margin_{i,0}$), which accounts for a significant portion of the variations in *RateGap*. Nevertheless, we estimate the regression with individual fixed effects in Table A2 of the Internet Appendix and find consistent results.

The coefficients before *RateGap* are both positive and statistically significant (t-statistic above 10). In terms of economic magnitude, the coefficient 0.0154 in Column (2) indicates that a one-standard-deviation increase in *RateGap* corresponds to a 15.4% increase in the prepayment indicator relative to its sample mean (15.4% = 0.628 × 0.0154 / 0.063). In Table A2 of the Internet Appendix, we replace the dependent variable *Prepay* over the 6-month window with monthly dummies, $Prepay_{t+1}, ..., Prepay_{t+6}$ to show the dynamics of the effects. We find that prepayment behavior is evenly distributed over the six month period with all t-statistic around 8.

An important implication from our hypothesis is that the effect of *RateGap* should be non-linear; that is, households' propensity to prepay decreases in LPR only if *RateGap* is positive, and no reaction when the mortgage rate remains lower than LPR. To test this important intuition, we estimate the following non-linear regression of prepayment on interest rate gap:

$$Prepay_{i,t+1\to t+6} = \alpha + \beta \cdot Max(RateGap, 0)_{i,t} + Controls + \mu_c + \gamma_t + \varepsilon_{i,t} \quad (3)$$

where $Max(RateGap, 0)_{i,t}$ equals $RateGap_{i,t}$ if $RateGap_{i,t}$ is larger than zero, and zero otherwise. Other variables and specifications are the same as those in Panel A.

Panel B of Table 2 presents the result. The coefficients before $Max(RateGap, 0)_{i,t}$ are all positive and statistically significant at the 1% level. For example, the coefficient is 0.0170 with a t-statistic of 18.43 in Column (3) which includes all control variables and the city-time fixed effects. Furthermore, all the R^2 values in Panel B are higher than their counterparts in Panel A. This suggests that $Max(RateGap, 0)_{i,t}$ has stronger explanatory power for prepayments than $RateGap_{i,t}$. The non-linear specification better captures households' prepayment behaviors and is thus used for our following analysis.[12]

We further illustrate this pattern in Figure 2, following the methodology of Berger et al. (2021). We estimate a regression of the prepayment dummy ($Prepay_{i,t+1\rightarrow t+6}$) on a series of 30-basis-point *RateGap* bins, ranging from -120 bps to $+180$ bps. We then calculate the fraction of prepayments in each gap bin based on the coefficients obtained from the regression. One can find that the positive correlation between prepayment and *RateGap* only shows up in the positive region of *RateGap*, while no correlation is observed with negative gaps. In addition, the "kink" around the zero rate gap motivates the use of $Frac > 0_{c,t}$, which is the proportion of existing mortgages with interest rates exceeding the LPR for city c in month t, as the key instrumental variable to identify the effectiveness of monetary policies (LPR adjustment) in the city-level analysis.

[Insert Figure 2 near here]

This non-linear pattern is similar to the findings of Berger et al. (2021), who show that US households also appear to prepay mortgage when the rate gap between their own and a new mortgage loan becomes positive. However, note that while the empirical patterns seem to be similar, the underlying economic mechanism can be distinct in China and the US. The key difference comes from the institutional settings of whether mortgage refinancing is allowed or not. We show that this difference can lead to contrasting implications for household behavior and the transmission of monetary policy, as evidenced in the following tests.

[12] In the following tests, we also report the results of the linear regression based on *RateGap* in either the robustness section or the Internet Appendix.

4.2.2. Alternative Benchmarks

The benchmark expected return used by households to evaluate their mortgage rates is not directly observable. While LPR is likely the most prominent reference rate, returns from popular investment products can also serve as alternative benchmarks. In this section, we use the returns of wealth management products (WMPs) as alternative reference points. According to the survey of PBC, more than 80% of Chinese households' financial wealth is invested in bank deposits and WMPs. With a market value of over 5.9 trillion USD in 2024, WMPs offered by commercial banks in China mostly invest in fixed incomes such as money market instruments, government bonds, and corporate bonds. These products provide households with relatively stable income and reasonable liquidity compared to higher-risk assets like equities. The decline in WMP returns is also frequently cited by the media as a key driver of mortgage prepayments[13]. For these reasons, we consider WMPs to be relevant benchmarks for evaluating mortgage rates.

We calculate the rate gaps using three benchmark returns of WMPs. We obtain data on benchmark returns of WMPs from Southern Finance Omnimedia Group (SFC)[14], one of China's largest WMP databases. The SFC database covers over 250,000 WMPs issued by more than 400 commercial banks. We select three key benchmark returns that are regularly featured in quarterly reports by SFC and other WMP data vendors: (1) the average benchmark return of newly issued WMPs, (2) the average realized return of WMPs maturing in the current quarter, and (3) the annualized return of cash-like WMPs. Conceptually, these returns serve as proxies for the expected return on new products, the realized return on existing products, and the return on the most liquid products, respectively.

[Insert Table 3 near here]

We report the results based on the three alternative returns and the LPR in Table 3. The sample period ends in December 2023, which corresponds to the most recent WMP data available to us.[15] Panel A shows the summary statistics of the rate gaps calculated

[13]For example, https://www.ft.com/content/9e0f1270-4d26-446a-9755-31d30e413dfb.

[14]Website: https://gym.sfccn.com/portal.

[15]This is why the result for the rate gap based LPR is different from that in Table 2 where the sample period ends in May 2024.

using these benchmark returns. On average, LPR is the highest, while the return of the cash-like WMPs is the lowest. This results in the smallest average rate gap for the LPR (0.25%) and the highest for the cash-like WMPs (1.01%). Due to these differences, the "kink" points of the three alternative gaps could deviate from that of the LPR-based gap, which is zero as shown in Figure 2. Therefore, we explore multiple critical values to identify the "kink" with the largest explanatory power for prepayment behavior. To do so, we use $Max(RateGap, X)$ as the key independent variable, where X takes on several selected values based on the distribution of each rate gap.

Panels B to D present the results. Two findings are notable. First, across multiple selected values of X, the coefficients on $Max(RateGap, X)$ for all three alternative benchmarks are positive and statistically significant at the 1% level. This implies that returns on WMPs indeed correlate with the true, unobserved benchmark used by households. Second, the regression model using $Max(RateGap\_LPR, 0)$ achieves the largest R^2 among all specifications. This suggests that, compared to other benchmarks, households are more likely to use (LPR + 0 bps) for evaluating their mortgage rates. This is also consistent with the "kink" in Figure 2. Based on this finding, we use the rate gap based on LPR for tests in the following sections.

4.2.3. Cross-sectional Analysis

As shown in Berger et al. (2021), when mortgage refinancing is available, low-income or financially constrained households are more responsive to a positive rate gap by repaying and refinancing their mortgages, as they have a greater incentive to reduce their interest expenses. In contrast, since refinancing is disallowed in China, households that choose to prepay are likely those with better financial conditions and sufficient savings or liquid investments. To verify this intuition, we perform a cross-sectional analysis in this section.

Specifically, we construct three dummy variables for high AUM, high credit score, and high education, respectively, each based on the 70th percentile of the sample. Then, we interact these dummy variables with $Max(RateGap, 0)$ in the baseline regression of Equation (3). Results are reported in Table 4. The coefficients before the interaction terms are all positive and significant at the 1% level. The economic magnitude is also meaningful; for example, in Column (1), the coefficient before $Max(RateGap, 0) \times HighAUM$ is 0.0165 (t-stat=9.75), whereas the coefficient before $Max(RateGap, 0)$ is 0.0119 (t-stat=16.06). This suggests that the top 30% high AUM households are 38.66% more responsive to rate gaps in terms of prepayment compared to other borrowers. The coefficients before the dummies themselves (high AUM, high credit score, and high education) are positive, which is expected as households with better financial conditions are more likely to prepay mortgages on average. We also visualize such effects in Figure 3 by repeating the analysis in Figure 2 for subsamples based on high versus low AUM in Panel A, high versus low credit scores in Panel B, and high versus low education in Panel C. The patterns shown in the figure are consistent with the regression results. Overall, the cross-sectional analysis offers additional insights into prepayment behaviors in the absence of refinancing, which sharply contrasts with the evidence from the US.

[**Insert Table 4 and Figure 3 near here**]

4.3. Saving and Consumption Behavior After Prepayment

Next, we examine how prepaying households adjust their saving and consumption behavior after making the prepayment. As discussed in Section 2.3, our mechanism implies that prepaying borrowers should significantly reduce their total savings and consumption after making the prepayment. The prediction, again, contradicts to implication of mortgage refinancing, which predicts more consumption afterwards due to lowered interest expenditure. Furthermore, our mechanism also suggests that the monetary policy (reducing LPR here) could be counterproductive in boosting borrowing and consumption from the household side.

Specifically, we examine households' total deposits and consumption in their bank accounts after the prepayment month. For each month, we compute the total deposits and total liquid assets (AUM) in each borrower's bank account. AUM include deposits and investments in wealth management products, mutual funds, and insurance-type products. We also calculate households' monthly total consumption made through their debit cards in the bank, as a majority of Chinese households do not have credit cards. We regress the log of total deposits, AUM, and consumption on a dummy variable, $AfterPrepay_{i,t}$, which equals one if borrower i has made at least one prepayment before month t. We include the same set of control variables as in Table 2. Results are reported in Table 5.

[Insert Table 5 near here]

Column (1) reports the effects on deposits. The coefficient for $AfterPrepay$ is -0.615, which is statistically significant at the 1% level. In terms of economic magnitude, it suggests that individuals' deposits decrease by 77.93% following mortgage prepayments. Column (2) shows a similar pattern, with a 72.14% decline in AUM after prepayments. In Column (3), where the dependent variable is consumption, the coefficient for $AfterPrepay$ is -0.0206 (t-value=-2.65). This indicates that households also reduce their consumption after prepaying their mortgages. These results are consistent with our hypothesis that households allocate a significant portion of their liquid assets to mortgage prepayments without refinancing, which leads to further reductions in consumption.

5. Policy Shock to Mortgage Rates

In this section, we employ a policy shock that reduces mortgage rates for some households to enhance the causal link between rate gaps and prepayments. On August 31, 2023, the PBC announced that eligible households could replace their existing mortgage rates with lower ones starting in October 2023. The goal of this policy is to "alleviate household interest rate burdens, stimulate consumption and investment, and reduce mortgage prepayments"[16]. In essence, this policy enables some households to perform a refinancing, while others remain unaffected. We use this policy shock to investigate the impacts of mortgage rate reductions on prepayments and consumption. The details of the policy are as follows.

To prevent real estate speculation, local mortgage margins for non-first homes in China are typically set higher than those for first homes. Moreover, these higher margins for non-first homes remain fixed for the life of the loan, even if the non-first home later becomes the household's only property. For example, if a household purchases Home A at time t and then Home B at time $t + 1$, the local margin for Home B (L_b) would be higher than that of Home

[16]See http://www.pbc.gov.cn/rmyh/3963412/3963426/5050299/index.html.

A (L_a). If the household sells Home A at time $t+2$, home B becomes the household's de facto "first" home. Logically, Home B should qualify for the lower local margin applicable to first homes. However, under the previous mortgage system, Home B's margin could not be adjusted to the lower rate of L_a.

The policy announced on August 31, 2023 addresses this issue by reducing the interest burden for households facing these circumstances. Specifically, it allows households to reset the local margin of Home B from L_b to the lower L_a, which effectively lower the mortgage rates for the households.[17] Since this policy applies only to households that meet specific criteria (e.g., those that previously owned multiple homes but now own only one), it lowers the rates for certain qualified mortgages, leaving others unchanged. According to our data, 25% of mortgages are affected by this policy, with an average interest rate reduction of 50 basis points for these loans. We employ this policy shock to conduct a formal difference-in-differences analysis on prepayments and consumption. The 25% mortgages affected by the policy constitute the treatment group, while the remaining loans serve as the control group.

5.1. *Mortgage Rate Reset and Mortgage Prepayments*

If the positive relationship between rate gap and prepayment is indeed causal, a negative shock to mortgage rates, which narrows the rate gaps, should lead to fewer mortgage prepayments. To test this prediction, we estimate the following DiD regression:

$$Prepay_{i,t} = \alpha + \beta \cdot Treat_i \times Post_t + Controls + \mu_i + \gamma_t + \varepsilon_{i,t} \tag{4}$$

where $Prepay_{i,t}$ is a dummy variable equal to one if individual i make a prepayment in month t, and zero otherwise. $Treat_i$ is a dummy variable equal to one if individual i qualifies for the interest rate reduction, and zero otherwise. $Post_t$ is a dummy variable equal to one if month t is after September 2023, and zero otherwise. We include all mortgages in China's four first-tier cities (Beijing, Shanghai, Shenzhen, and Guangzhou). The sample period is October 2022 to May 2024.

[17] This is a "semi-refinancing" because the eligible household can only reset the local margin to L_a which was the lowest at the time the mortgage was issued. However, the household cannot reset it to the current local margin, which could be even lower than L_a.

[Insert Table 6 near here]

Table 6 presents the results of the DiD regression. In Column (2), which includes all control variables, the coefficient of the interaction term, $Treat_i \times Post_t$, is -0.005 and statistically significant at the 1% level (t-value=-5.76). Economically, this coefficient suggests that, compared to households unaffected by the policy, affected households experience a 25.51% greater reduction in prepayments relative to the sample mean (25.51%=0.005/0.0196). Consistent with our hypothesis, a salient negative shock to the rate gaps leads to a significant decrease in the prepayment intentions.

To examine the parallel trend assumption, we plot the dynamic effects of the policy on prepayments in Panel A of Figure 4. We include a series of interaction terms, $Treat_i \times Post_k$, where k indicates the number of quarters relative to the event month. We use k=-1 as the benchmark quarter. Panel A presents the coefficients of these interaction terms along with their confidence intervals. The coefficients for the post-event periods are negative and statistically significant, while those for the pre-event periods are indistinguishable from zero. These patterns provide strong evidence supporting the parallel trend assumption.

[Insert Figure 4 near here]

5.2. Mortgage Rate Reset and Household Consumption

We next examine the impact of the policy on household consumption. If mortgage prepayments indeed constrain household consumption, we expect consumption to increase following a policy that narrows rate gaps and discourages prepayments. We estimate the same DiD regression as in Table 6. We use the natural logarithm of debit card consumption, $LogConsumption_{i,t}$, as the dependent variable. We focus on debit card consumption because most clients in our sample do not have credit cards. The low adoption rate of credit cards is not unique to our sample but reflects a common phenomenon in China.[18]

[Insert Table 7 near here]

[18] For instance, according to Statista, the number of credit cards per capita is 0.57 for China and 3.2 for the United States, respectively.

The results in Table 7 show that households increase their consumptions following the mortgage rate reduction. For instance, in Column (2), the coefficient of the interaction term is 0.0068, which is statistically significant at the 1% level (t-statistic=2.72). In terms of economic magnitude, this coefficient suggests that affected households experience a 0.68% greater increase in consumption compared to unaffected households. We also conduct a parallel trend analysis in Panel B of Figure 4. The figure shows that affected households exhibit significantly larger increases in consumption than unaffected households during the post-event periods, while no discernible differences are observed during the pre-event periods. These findings validate the parallel trend assumption.

Overall, the results in this section support a causal link between rate gaps and both prepayments and consumption. Furthermore, the evidence suggests that policies aimed at reducing frictions in mortgage refinancing can enhance the transmission of expansionary monetary policies. This provides direct policy guidance on how to make monetary policy effective through the household mortgage channel.

6. Implications to Monetary Policy Transmission

In the previous section, we present evidence that Chinese households tend to prepay their mortgages using savings when the LPR is adjusted below their mortgage rate, leading to a reduction in consumption. In this section, we extend the analysis to the city level to examine the macroeconomic consequences of the monetary policy.

6.1. Interest Rate Gap and Mortgage Prepayment: City-level Evidence

We first extend the baseline loan-level analysis in Table 2 to the city level. The dependent variable, labeled as $PrepayCount_{c,t+1\rightarrow t+6}$, is the number of mortgage prepayments scaled by the total number of mortgage repayments in city c averaged over month $t+1$ to $t+6$. We also calculate $RateGap\_City_{c,t}$, which is the difference between the average interest rate of existing mortgages in city c for month t ($M\_City_{c,t}$) and LPR_t. Specifically, we estimate the following regression,

$$PrepayCount_{c,t+1\to t+6} = \alpha + \beta \cdot RateGap\_City_{c,t} + Controls + \mu_c + \gamma_t + \varepsilon_{c,t} \quad (5)$$

Controls represent a set of macroeconomic variables such Purchasing Managers' Index (PMI), the changes in CPI, GDP growth, GDP per capita, the average housing price, and the monthly change of housing price. We also include city and year-month fixed effects. The time fixed effects can rule out the possible effect at the country level; for example, it could be that the adjustment of LPR contains information about the perspective of the future economy, which in turn leads to more mortgage prepayment. Similar to our individual analysis, the identification relies on the heterogeneity of each city's current mortgage rate, or more precisely, on the fixed component, i.e., the local margin.

[Insert Table 8 near here]

Regression results are presented in Table 8 and consistent with our findings at the loan-level in Table 2. For instance, in Column (2) of Panel A, where all control variables and fixed effects are included, the coefficient before *RateGap_City* equals 0.0040 (t-statistic=7.34). This suggests that a one-standard-deviation increase in *RateGap_City* is associated with a 14.4% increase in the *PrepayCount* ratio relative to the sample mean. In Panel B, we present the result separately for each month from $t+1$ through $t+6$. The coefficients before *RateGap_City* remain positive and statistically significant across all these months. In addition to the count-based measure, we also calculate the ratio of the yuan-value of mortgage prepayments to the total value of mortgage repayments as an alternative dependent variable. Table A5 in the Internet Appendix shows our results are robust to using the value-based prepayment measure.

6.2. $Frac > 0$ and Mortgage Prepayment: City-level Evidence

To strengthen our identification strategy, we use an alternative measure of rate gaps that is less correlated with current economic conditions. Specifically, we follow the methodology of Berger et al. (2021) and calculate the proportion of existing mortgages with interest rates exceeding the LPR for each city-month, denoted as $Frac > 0_{c,t}$. This is motivated by Figure 2, which shows that the effect of $RateGap_{i,t}$ on prepayment is significant only when $RateGap_{i,t}$ is positive. Using $Frac > 0$ thus exploits the "kink" in $RateGap_{i,t}$'s effect on prepayment decisions and buttresses the identification power of our tests. More importantly, as discussed in Section 2, the cross-sectional variations in $Frac > 0$ are determined by homeowners' local margins at the time mortgages were issued, which are plausibly not correlated with households' current expectations about future economic conditions. This makes $Frac > 0$ less susceptible to endogeneity concerns.

[Insert Table 9 near here]

We first use $Frac > 0$ instead of $RateGap\_City$ as the key explanatory variable. The average of $Frac > 0$ equals 81.0% with a standard deviation of 16.2%. As shown in Column (3) of Table 9, the coefficient before $Frac > 0$ is positive and highly significant, with a t-statistic of 5.78. Economically, a one-standard-deviation increase in the fraction of the population with rates higher than the LPR is associated with a 14.0% increase in prepayment ratio relative to the sample mean. The results are consistent with those based on rate gaps.

We next compute multiple $Frac > X$ for additional analyses, where X takes values of -60 bps, -30 bps, +30 bps, and +60 bps. The rationale is that the true benchmark used by households is unobservable and may differ from (LPR+0 bps). To explore this possibility, we use (LPR+X bps) as alternative benchmarks, resulting in multiple $Frac > X$ measures. The results are presented in the remaining columns of Table 9. We find significant and positive coefficients for $Frac > -60bps$, $Frac > -30bps$, and $Frac > +30bps$. Notably, the R^2 from the regression using $Frac > 0$ is significantly higher than those using other $Frac > X$ measures. This suggests that $Frac > 0$ has the strongest explanatory power for prepayments, indicating that households are likely using the LPR as the benchmark to evaluate their mortgage rates. Based on these findings, we use $Frac > 0$ as the instrumental variable to examine the causal impacts of mortgage prepayments on consumption and total lending in the following analysis.

6.3. *Mortgage Prepayment and Household Consumption: City-level Evidence*

Our hypothesis implies that borrowers tend to reduce their consumption and deposits after making mortgage prepayments. The key ingredient driving this behavior is the financial friction in mortgage refinancing: households have to finance their prepayments using their savings. In comparison, when refinancing is allowed, refinancing a mortgage with a lower interest rate can lead to increased consumption, as evidenced by data from the United States. In the previous section, using account-level data, we show that households' deposit levels significantly decrease after prepayment. In this section, we use the city-level consumption data from UnionPay to examine the effect of prepayment on consumption.

The main challenge for this analysis is to identify the causal effect of LPR adjustments on household consumption through the mortgage prepayment channel. Other factors, which may not be related to monetary policy, could also drive the correlation between mortgage prepayment and reduced consumption. For example, it is possible that a city's residents are pessimistic about the local economy, leading to consumption reduction and household deleveraging (i.e., prepaying mortgage with savings). Such a channel is compelling, and we acknowledge that it could partially explain the observed correlation between prepayment and consumption. However, we are more interested in the transmission mechanism of monetary policies.

To address this challenge, we adopt an instrumental variable (IV) approach. Specifically, we instrument the prepayment variable, $PrepayCount_{c,t}$, with $Frac > 0_{c,t-1}$, and examine its impact on the consumption growth rate from months $t+1$ to $t+6$. The exclusion restriction is that $Frac > 0_{c,t-1}$ is not correlated with mortgage borrowers' expectations of the future local economy in city c. We argue that this assumption is plausible. $Frac > 0_{c,t-1}$ mainly depends on the distribution of the local margins of the borrowers, which are fixed and determined by the distribution of the timing of mortgage issuance and the local policies at the time of issuance. It is not obvious that this is related to borrowers' current expectations of the future economy.

Specifically, we estimate the following 2-stage IV regression,

$$\Delta Consumption_{c,t+1\rightarrow t+6} = \alpha + \beta \cdot \widehat{PrepayCount}_{c,t} + Controls + \mu_c + \gamma_t + \varepsilon_{c,t} \tag{6}$$

where the dependent variable is the log change of total consumption of city c from month $t+1$ to month $t+6$. Total consumption is measured by the total spending via UnionPay bank cards. Other control variables and fixed effects are the same as the regression of Equation (5).

[Insert Table 10 near here]

Table 10 presents the results. Columns (1) and (2) present the results of the first-stage and second-stage regressions, respectively. In the first-stage regression, $Frac > 0$ exhibits a strong positive correlation with the mortgage prepayment ratio. This is consistent with the findings in Table 9. The F-stat equals 28.30 and rules out the concern about a weak IV.

In the second-stage regression, the coefficient before $PrepayCount$ is -31.9645 with a t-statistic $= -4.70$. This suggests that mortgage prepayments driven by lowered LPR make households reduce their subsequent consumption. The economic magnitude is also substantial: a one-standard-deviation increase in the fraction of prepayments is associated with a 52.8% ($= 0.006 \times 31.9645/0.363$) standard deviation decrease in consumption growth. In Column (3), we perform an OLS regression of consumption growth on prepayment. The coefficient before $PrepayCount$ is smaller in magnitude, at -20.0648 (t-statistic$= -5.30$). Overall, the findings suggest that low interest rates curtail, rather than stimulate, household consumption, through the household prepayment channel. This result is contrary to the findings in the US and the objectives of the expansionary monetary policy.

Moreover, we examine the heterogeneity in the types of consumption to provide further evidence supporting our channel. Our hypothesis implies that the reduction should be more pronounced in non-necessity consumption. We adopt two categorizations to distinguish between necessity and non-necessity consumption, based on the data provided by UnionPay.

The first categorization differentiates between discretionary and essential consumption. We expect discretionary consumption to be more significantly affected by the prepayment-induced liquidity shock. According to the data provided by UnionPay, essential consumption includes food, gasoline, utilities, household services, and telephone services. Discretionary consumption covers alcohol, tobacco, cars, electronic devices, entertainment, and inter-city transportation. Panel A of Table 11 presents the results. For both IV and OLS regressions, the coefficients before $PrepayCount$ are larger in magnitude and statistically more significant for discretionary consumption than for essential consumption. For instance, in the IV results, the coefficient of $PrepayCount$ is -11.4664 (t-statistic$= -1.17$) for essential consumption, while it is -45.9138 (t-statistic$= -4.16$) for discretionary consumption. This confirms our prediction.

The second categorization is based on the size of the spending. Larger expenditures are more likely related to the consumption of durable goods, luxury activities, and similar items. Homeowners' large consumption is also more affected or delayed by mortgage prepayments compared to smaller expenditures. We use 1,000 RMB as the cutoff to define small versus large spending. The results in Panel B show that in both IV and OLS regressions, large-scale consumption is more significantly affected by mortgage prepayments than smaller expenditures. For example, the coefficient of $PrepayCount$ is -6.1824 (t-statistic$= -0.99$) for small consumption, while it is -31.5907 (t-statistic$= -4.66$) for large consumption.

[**Insert Table 11 near here**]

Overall, the evidence in this section supports our hypothesis that the lowered LPR rates lead to household consumption reduction through the mortgage prepayment channel, which is a counterproductive policy consequence.

6.4. Policy Implications

In the final section, we discuss the implications of our findings on the effectiveness of monetary policies in China. In our city-level analysis, we use $Frac > 0$ as an IV to identify the causal effect of LPR adjustments on household consumption through the mortgage prepayment channel. However, an economically more meaningful way to think of $Frac > 0$ is to view it as a measure of the frictions in monetary policy transmission. That is, for cities where more borrowers pay mortgage rates higher than LPR, reductions in LPR are more likely to be counterproductive in boosting household borrowing and consumption. This interpretation contrasts with that of Berger et al. (2021), who view $Frac > 0$ as a measure of monetary policy "space". Again, the key factor driving this difference is the availability of effective refinancing options within the mortgage system.

We illustrate this intuition by estimating the following OLS regression,

$$\Delta Consumption_{c,t+1\rightarrow t+6} = \alpha + \beta HighFrac_{c,t-1} \cdot \Delta LPR_t + Controls + \mu_c + \gamma_t + \varepsilon_{c,t} \qquad (7)$$

where $HighFrac_{c,t-1}$ is a dummy variable that equals one if $Frac > 0_{c,t-1}$ is above the 70th percentile of the sample, and zero otherwise. ΔLPR_t refers to the monthly changes in LPR. Controls include $Frac > 0_{c,t-1}$ and the same set of the control variables and fixed effects as in Table 10. The point estimate of β gauges how the sensitivity between LPR changes and subsequent consumption varies with $HighFrac$. The sensitivity between LPR changes and subsequent consumption ought to be negative, provided an effective monetary policy.[19] If $HighFrac$ measures "frictions" in monetary policy transmission, we would expect β to be positive. The results presented in Table 12 are consistent with this conjecture; the coefficient before the interaction term is 0.4104 (t-statistic = 2.34). This suggests that cutting interest rates to stimulate consumption is indeed less effective in cities with a higher proportion of households facing significant rate gaps.

[Insert Table 12 near here]

Finally, we examine other broader macroeconomic consequences beyond the household sector. We have shown that expansionary monetary policy leads households to prepay mortgage loans. One might question whether less mortgage borrowing from households necessarily translates to lower aggregate lending. It is possible that funds from these prepayments could be redirected to other sectors or even back to households through alternative loan types, such as credit cards and short-term loans. From the perspective of central banks, the aggregate effect is of more importance. If these alternative lending channels outweigh the impact of mortgage prepayments, the monetary policy transmission could still be effective.

[19] ΔLPR_t is subsumed by the year-month fixed effects.

To answer this question, we examine the impacts of prepayments on total lending by all financial institutions in a city. We replace the dependent variable in Equation (6) with $\Delta Lending_{c,t+1\to t+6}$, the growth rate of total lending of city c from month $t+1$ to month $t+6$. That is, we conduct IV and OLS regressions as follows,

$$\Delta Lending_{c,t+1\to t+6} = \alpha + \beta \cdot \widehat{PrepayCount}_{c,t} + Controls + \mu_c + \gamma_t + \varepsilon_{c,t} \tag{8}$$

[Insert Table 13 near here]

Table 13 presents the results. The F-stat from the first-stage regression equals 12.39, ruling out the concern of weak IV. In the second stage of the IV regression, the coefficient before $PrepayCount$ is -1.1934 with a t-statistic of -5.01. The results are similar for the OLS regression in Column (3). This suggests that mortgage prepayments following interest rate cuts lead to a reduction in aggregate lending provided by financial institutions. This is another counterproductive consequence of expansionary monetary policies.

7. Conclusion

Despite of restrictions on mortgage refinancing, Chinese households prepaid an unprecedented amount of mortgage loans between 2021 and 2024, when the government cut interest rates to combat economic slowdown. Using loan-level data from a large commercial bank in China, we find that households are likely to prepay when the gap between their own mortgage rate and the benchmark rate becomes positive and increases. Evidence further suggests that households prepay with their savings (rather than through refinancing), and the prepayment is associated with household deleverage and consumption reduction. Combining with the data of UnionPay card spending, we find macro-level evidence that as the national lending rate decreases, cities with more mortgage borrowers having a positive rate gap tend to experience greater prepayment, consumption reduction, and lending contraction, suggesting counter-productive monetary policy transmission.

A natural question arises: in the presence of refinancing restrictions, how can monetary policy be made effective through the household mortgage channel? Our analysis of the shock to mortgage rates in Section 5 provides some policy insights. Following a reduction in mortgage rates, affected borrowers immediately increase their consumption, particularly in discretionary categories and non-durable goods. Our study indicates that enabling household mortgage rates to fluctuate with the central bank's benchmark rate is essential for effective monetary policy transmission. Deregulation on mortgage refinancing might also help but probably would not be as effective as floating mortgage rate, as refinancing is costly and not every borrower would refinance based on the US evidence.

References

Agarwal, S., Deng, Y., Gu, Q., He, J., Qian, W., Ren, Y., 2022. Mortgage Debt, Hand-to-Mouth Households, and Monetary Policy Transmission. Review of Finance 26, 487–520.

Agarwal, S., Green, R. K., Rosenblatt, E., Yao, V., 2015. Collateral pledge, sunk-cost fallacy and mortgage default. Journal of Financial Intermediation 24, 636–652.

Agarwal, S., Qian, W., Seru, A., Zhang, J., 2020. Disguised corruption: Evidence from consumer credit in china. Journal of Financial Economics 137, 430–450.

Agarwal, S., Rosen, R. J., Yao, V., 2016. Why Do Borrowers Make Mortgage Refinancing Mistakes? Management Science 62, 3494–3509.

Andersen, S., Campbell, J. Y., Nielsen, K. M., Ramadorai, T., 2020. Sources of Inaction in Household Finance: Evidence from the Danish Mortgage Market. American Economic Review 110, 3184–3230.

Auclert, A., 2019. Monetary Policy and the Redistribution Channel. American Economic Review 109, 2333–2367.

Badarinza, C., Campbell, J. Y., Ramadorai, T., 2016. International Comparative Household Finance. Annual Review of Economics 8, 111–144.

Bajo, E., Barbi, M., 2018. Financial illiteracy and mortgage refinancing decisions. Journal of Banking & Finance 94, 279–296.

Beraja, M., Fuster, A., Hurst, E., Vavra, J., 2019. Regional Heterogeneity and the Refinancing Channel of Monetary Policy*. The Quarterly Journal of Economics 134, 109–183.

Berger, D., Milbradt, K., Tourre, F., Vavra, J., 2021. Mortgage Prepayment and Path-Dependent Effects of Monetary Policy. American Economic Review 111, 2829–2878.

Bhutta, N., Keys, B. J., 2016. Interest Rates and Equity Extraction during the Housing Boom. American Economic Review 106, 1742–1774.

Caballero, R. J., 1990. Consumption puzzles and precautionary savings. Journal of Monetary Economics 25, 113–136.

Chen, H., Michaux, M., Roussanov, N., 2020a. Houses as ATMs: Mortgage Refinancing and Macroeconomic Uncertainty. The Journal of Finance 75, 323–375.

Chen, H., Qian, W., Wen, Q., 2021. The Impact of the COVID-19 Pandemic on Consumption: Learning from High-Frequency Transaction Data. AEA Papers and Proceedings 111, 307–311.

Chen, H., Qian, W., Wen, Q., 2023a. Singles Day and Consumer Spending Offline.

Chen, K., Gao, H., Higgins, P., Waggoner, D. F., Zha, T., 2023b. Monetary Stimulus amidst the Infrastructure Investment Spree: Evidence from China's Loan-Level Data. The Journal of Finance 78, 1147–1204.

Chen, K., Ren, J., Zha, T., 2018. The Nexus of Monetary Policy and Shadow Banking in China. American Economic Review 108, 3891–3936.

Chen, Z., He, Z., Liu, C., 2020b. The financing of local government in China: Stimulus loan wanes and shadow banking waxes. Journal of Financial Economics 137, 42–71.

Christelis, D., Georgarakos, D., Jappelli, T., Van Rooij, M., 2020. Consumption Uncertainty and Precautionary Saving. The Review of Economics and Statistics 102, 148–161.

Cloyne, J., Ferreira, C., Surico, P., 2020. Monetary Policy when Households have Debt: New Evidence on the Transmission Mechanism. The Review of Economic Studies 87, 102–129.

Deng, Y., Quigley, J. M., Van Order, R., 2000. Mortgage Terminations, Heterogeneity and the Exercise of Mortgage Options. Econometrica 68, 275–307.

Di Maggio, M., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A., Yao, V., 2017. Interest Rate Pass-Through: Mortgage Rates, Household Consumption, and Voluntary Deleveraging. American Economic Review 107, 3550–3588.

Di Maggio, M., Kermani, A., Palmer, C., 2016. Unconventional Monetary Policy and the Allocation of Credit. SSRN Electronic Journal .

Dunn, K. B., McConnell, J. J., 1981. Valuation of GNMA Mortgage-Backed Securities. The Journal of Finance 36, 599–616.

Eichenbaum, M., Rebelo, S., Wong, A., 2022. State-Dependent Effects of Monetary Policy: The Refinancing Channel. American Economic Review 112, 721–761.

Garriga, C., Kydland, F. E., Šustek, R., 2017. Mortgages and Monetary Policy. The Review of Financial Studies 30, 3337–3375.

Gourinchas, P.-O., Parker, J. A., 2001. The Empirical Importance of Precautionary Saving. American Economic Review 91, 406–412.

Green, J., Shoven, J. B., 1986. The Effects of Interest Rates on Mortgage Prepayments. Journal of Money, Credit and Banking 18, 41.

Greenwald, D., 2018. The Mortgage Credit Channel of Macroeconomic Transmission.

Huang, Y., Ge, T., Chu, W., 2019. Monetary policy framework and transmission mechanism. Handbook of China's Financial System .

Iacoviello, M., 2005. House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle. American Economic Review 95, 739–764.

Kaplan, G., Violante, G. L., 2014. A Model of the Consumption Response to Fiscal Stimulus Payments. Econometrica 82, 1199–1239.

Kaplan, G., Violante, G. L., Weidner, J., 2014. The Wealthy Hand-to-Mouth. NBER Working Paper Series .

Keys, B. J., Pope, D. G., Pope, J. C., 2016. Failure to refinance. Journal of Financial Economics 122, 482–499.

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

Miles, D., 2004. The UK Mortgage Market: Taking a Longer-Term View .

Parker, J. A., Preston, B., 2005. Precautionary Saving and Consumption Fluctuations. American Economic Review 95, 1119–1143.

Rubio, M., 2011. Fixed- and Variable-Rate Mortgages, Business Cycles, and Monetary Policy. Journal of Money, Credit and Banking 43, 657–688.

Schwartz, E. S., Torous, W. N., 1989. Prepayment and the Valuation of Mortgage-Backed Securities. The Journal of Finance 44, 375–392.

Xiong, W., 2023. Derisking Real Estate in China's Hybrid Economy. NBER Working Paper Series .

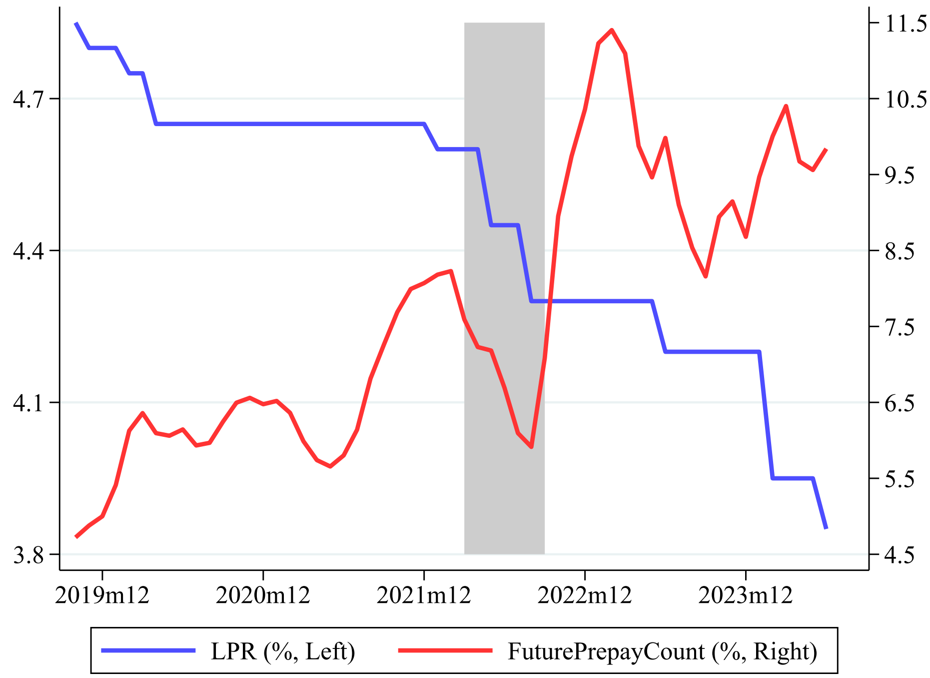


Fig. 1. The time series of mortgage prepayments and LPR

This figure plots the monthly LPR and the future mortgage prepayment percentage from October 2019 to May 2024. The future mortgage prepayment percentage for month t, $FuturePrepayCount_t$, is the ratio of the total number of prepayments to total number of mortgage repayments between month $t+1$ and month $t+6$. The shaded bar indicates the periods of widespread lockdowns in China during the COVID-19 pandemic.

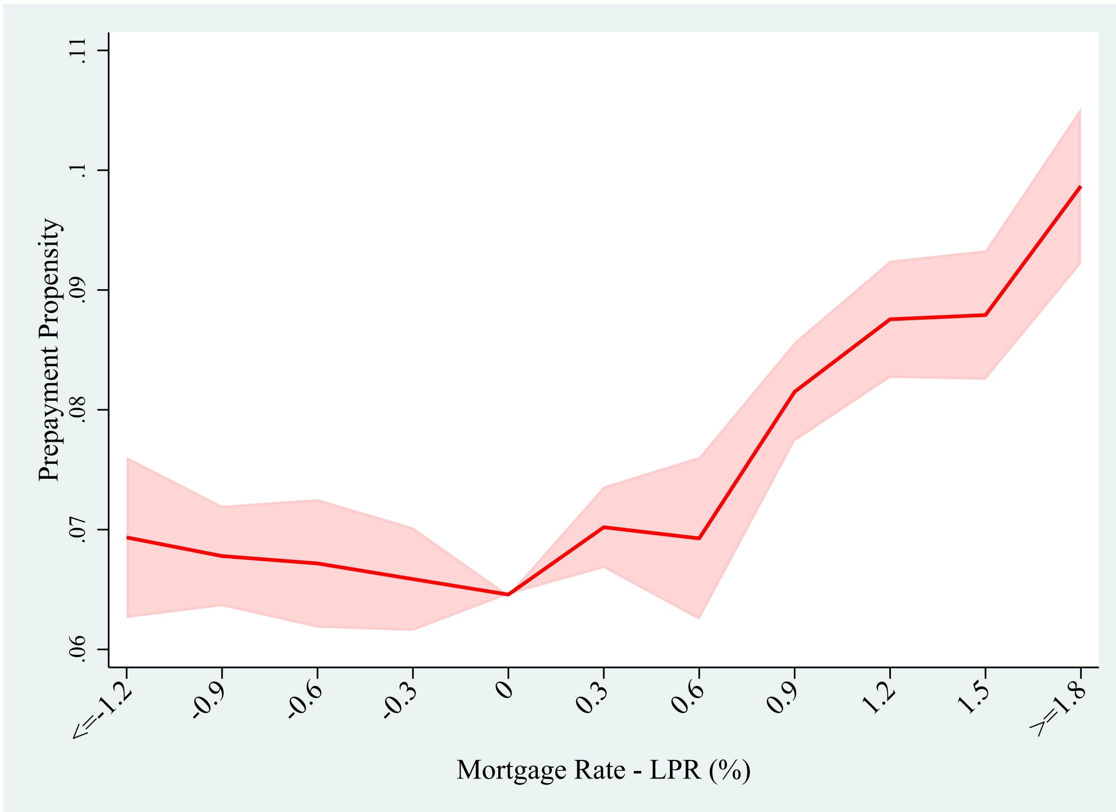
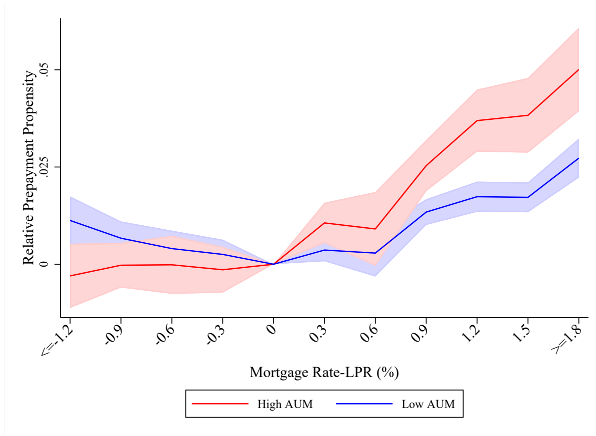


Fig. 2. Interest rate gaps and mortgage prepayments

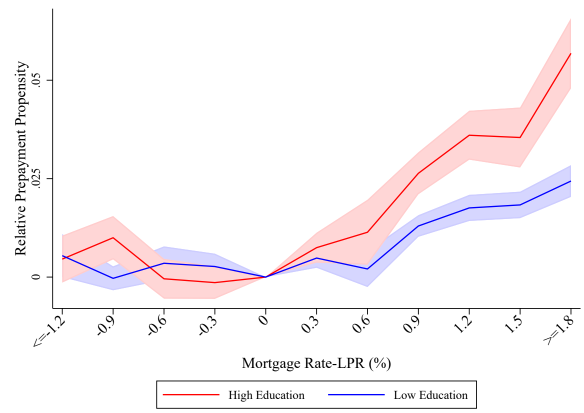
This figure presents the fraction of individuals making prepayment within each 30-bps interest rate gap bin. The x-axis denotes the 30-bps gap bins, which are based on the difference between households' mortgage rates and the LPR. The y-axis represents the fraction of individuals making prepayment (in decimal) for each gap bin, as well as their 95% confidence intervals. These fractions are estimated using the following regression:

$$\text{Prepay}_{i,(t+1,t+6)} = \beta_{\text{gapbin}}\, 1(\text{RateGap bin})_{i,t} + \text{Controls}_{i,t} + \varepsilon_{i,t}$$

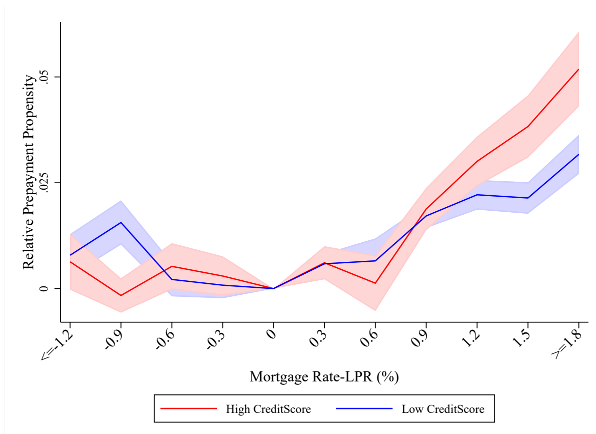
The dependent variable is a dummy variable which equals one if individual i prepays his or her mortgage between month $t+1$ and $t+6$, and zero otherwise. $1(\text{RateGap bin})_{i,t}$ is a dummy variable that indicates the 30-bps gap bins spanning from -120 bps to +180 bps. The control variables include loan to value (LTV), LTV^2, mortgage age dummies, log AUM, gender dummies, education, internal credit score, and city fixed effects. All variables are defined in Appendix A.



(a) Panel A: By AUM



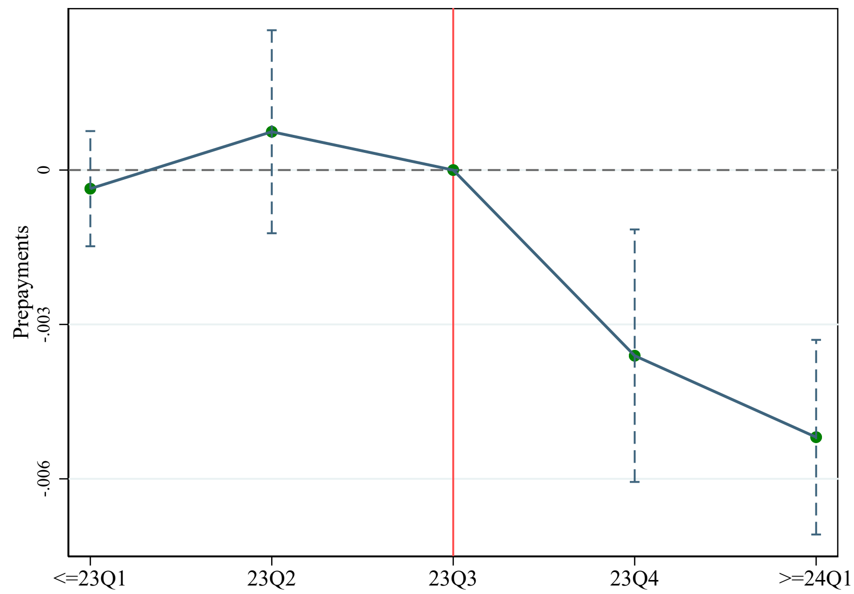
(b) Panel C: By Education



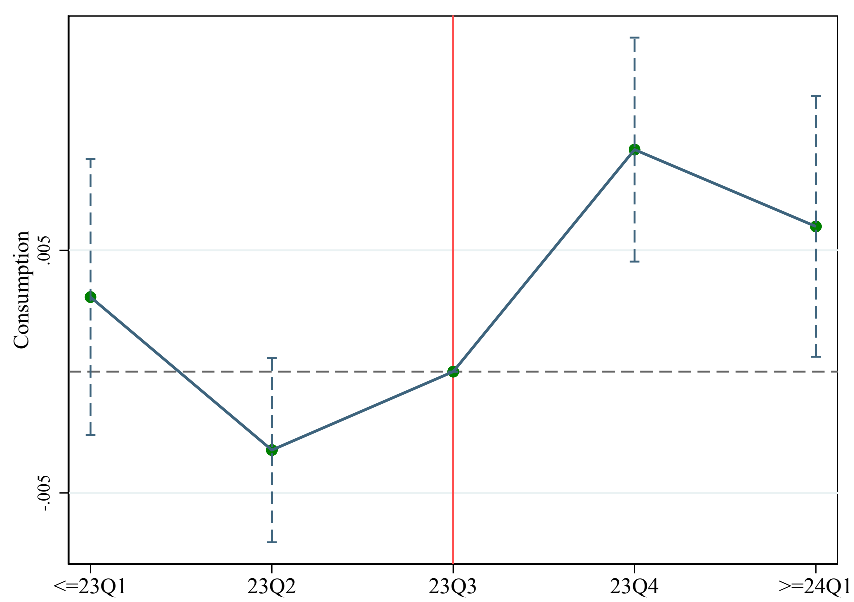
(c) Panel B: By CreditScore

Fig. 3. Interest rate gaps, household characteristics, and mortgage prepayments

This figure presents the fraction of individuals making prepayment within each 30-bps interest rate gap bin for different subsamples. For clarity, we use the fraction of the zero-rate gap bin as the benchmark and calculate the relative fraction for each rate gap bin. The fractions are estimated using the same specifications in Figure 2. In Panel A, we present the results for the high-AUM individuals (AUM>70th percentile) and low-AUM individuals separately; In Panel B, we present the results for the high-credit score individuals (credit score>70th percentile) and low-credit score individuals separately; In Panel C, we present the results for the high-education individuals (education level≥Bachelor) and low-education individuals separately.



(a) Panel A: Prepayments



(b) Panel B: Consumption

Fig. 4. Parallel-trend analysis

This figure presents dynamic treatment effects of the local margin reset policy. We estimate the policy's dynamic effects on prepayments and consumption by including a series of interaction terms, $Treat_i * Post_k$, in the DiD regression. The benchmark is the third quarter of 2023, which is the quarter in which the policy was announced. We plot the coefficients on the interaction terms and their corresponding 95% confidence intervals. All regressions include individual fixed effects and city-time fixed effects. Standard errors are clustered at the year-month level.

Table 1: Summary statistics

This table presents the summary statistics of the main variables. All variables are defined in Appendix A. Panels A presents the summary statistics for the main variables used in the loan-level analyses. Panel B compares the average characteristics of individuals who did not make any mortgage prepayments to those who made at least one mortgage prepayment during the sample period. The sample consists of 100,000 randomly selected clients from the commercial bank, with no missing values for the main variables. Panel C presents the summary statistics for the main variables used in the city-level analyses. All variables are defined in Appendix A. The sample period spans from October 2019 to May 2024.

Panel A: Variables for loan-level analysis

	N	Mean	STD	P25	P50	P75
$Prepay_{t+1\rightarrow t+6}$	4400112	0.063	0.243	0	0	0
$Prepay_t$	4400112	0.011	0.106	0	0	0
M	4391403	4.750	0.690	4.200	4.750	5.240
$RateGap$	4391403	0.279	0.628	-0.040	0.250	0.695
$Gap\_MaturingWMP$	3838091	0.982	0.782	0.490	1.000	1.485
$Gap\_CashLikeWMP$	3838091	2.113	0.671	1.790	2.090	2.570
$Gap\_NewlyIssuedWMP$	3838091	0.895	0.644	0.538	0.900	1.318
Age	4208692	38.926	8.342	33.000	38.000	44.000
$HighEduc$	4400112	0.292	0.455	0.000	0.000	1.000
$ISMale$	4400112	0.640	0.480	0.000	1.000	1.000
$CreditScore$	4397213	775	59	767	784	801
$LogAUM$	4400112	7.592	2.538	6.288	7.698	9.144
LTV	4397768	0.434	0.190	0.290	0.465	0.590
$MortgageAge$	4400112	5.779	3.345	3.000	5.000	8.000
$HousingPRC$	4400112	11399	9429	6093	8682	13269
$DeltaPRC$	4400112	0.001	0.113	-0.035	0.000	0.037

Panel B: Individuals without prepayments vs individuals with prepayments

	IDs without Prepayment	IDs with Prepayment
$NumberofIndividuals$	62461	37539
$CreditScore$	772.394	780.942
$ISMale$	0.657	0.602
Age	39.320	37.939
$MortgageAge$	6.116	4.909
$HighEduc$	0.258	0.372
AUM	17888.900	25543.490
$HouseArea$	105.113	107.660
$HouseValue$	723893.100	1017560.810
$INTRT$	4.699	4.871
$RateGap$	0.256	0.333
LTV	0.440	0.419
$HousingPrc$	10049.000	11518.000
$DeltaPRC$	0.001	0.002
$NormalPayment$	2694.160	3489.84
$Prepayments$	NA	170430.090

Panel C: Variables for city-level analysis						
	N	Mean	STD	P25	P50	P75
$PrepayCount_{t+1\rightarrow t+6}$	12950	0.009	0.005	0.006	0.008	0.011
$PrepayCount_t$	12950	0.010	0.006	0.007	0.009	0.011
$PrepayValue_t$	12950	0.172	0.105	0.105	0.151	0.209
M_City	12950	4.976	0.363	4.859	5.017	5.180
$RateGap\_City$	12950	0.464	0.323	0.300	0.470	0.630
$Frac{>}0$	12950	0.810	0.162	0.758	0.845	0.918
CPI	12950	2.315	1.290	1.300	2.100	2.800
GDP Growth	12950	0.007	0.048	-0.022	-0.001	0.037
$LogGDPPerCap$	12950	10.983	0.484	10.619	10.919	11.314
PMI	12950	49.585	2.646	49.000	50.100	50.800
$\Delta HousingPrice$	12950	0.001	0.085	-0.031	0.000	0.033
$LogHousingPrice$	12950	8.837	0.454	8.549	8.746	9.004
$\Delta Lending_{t+1\rightarrow t+6}$	6368	0.006	0.006	0.002	0.006	0.010
$\Delta Consumption_{t+1\rightarrow t+6}$	6426	-0.019	0.363	-0.204	-0.057	0.090

Table 2: Interest rate gaps and mortgage prepayments

This table presents the effects of interest rate gaps on mortgage prepayments at the loan level. In Panel A, the dependent variable is $Prepay_{i,t+1\rightarrow t+6}$, a binary indicator equal to one if individual i prepays their mortgage between months $t+1$ and $t+6$, and zero otherwise. The key independent variable, $RateGap_{i,t}$, is the mortgage rate of individual i minus the LPR in month t. In Panel B, we replace $RateGap_{i,t}$ with $Max(RateGap, 0)_{i,t}$ which equals the greater value of $RateGap_{i,t}$ and zero. Individual-level control variables include individual i's loan-to-value ratio and its quadratic term, credit score, log of total assets in the commercial bank, mortgage age dummies, dummies for high education and gender. Macro-level control variables include the GDP growth rate, GDP Per capita, the average price of new houses, and the average change in the housing prices in individual i's city in month t. All variables are defined in Appendix A. We include city fixed effects and year-month fixed effects in Columns (1) and (2), and city-time fixed effects in Column (3). The sample is from October 2019 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Interest rate gap and prepayment

	(1)	(2)	(3)
		$Prepay_{t+1\rightarrow t+6}$	
RateGap	0.0131***	0.0154***	0.0189***
	(10.82)	(14.85)	(14.89)
Log(AUM)		0.0048***	0.0048***
		(16.23)	(16.73)
LTV		-0.0911***	-0.0909***
		(-22.13)	(-22.12)
LTV^2		0.0116***	0.0121***
		(4.25)	(4.44)
CreditScore		0.0000	0.0000
		(0.30)	(0.34)
HighEducation		0.0148***	0.0154***
		(12.59)	(13.00)
Male		-0.0100***	-0.0103***
		(-31.40)	(-29.21)
GDP Growth		0.0009	
		(0.14)	
GDP Per Cap		-0.0192***	
		(-6.35)	
Log(PRC)		0.0034	
		(1.65)	
Delta PRC		0.0000	
		(1.19)	
City FE	YES	YES	-
Year-Month FE	YES	YES	-
City-Time FE	NO	NO	YES
Within R^2	0.10%	0.91%	0.51%
N	4391404	4391404	4391404

Panel B: Positive interest rate gap and prepayment			
	(1)	(2)	(3)
		$Prepay_{t+1 \rightarrow t+6}$	
$Max(RateGap, 0)$	0.0203***	0.023981***	0.01704***
	(8.99)	(15.71)	(18.43)
Controls	NO	YES	YES
City FE	YES	YES	-
Time FE	YES	YES	-
City-Time FE	NO	NO	YES
Within R^2	0.12%	0.92%	0.58%
N	4391404	4391404	4391404

Table 3: Alternative rate gaps and prepayment

This table presents results of the baseline regressions using alternative interest rate gaps. $RateGap_{i,t}$ is the mortgage rate of individual i minus the LPR in month t. $Max(RateGap, X)_{i,t}$ equals the greater value of $RateGap_{i,t}$ and X bps. $RateGap\_Cash_{i,t}$ is the mortgage rate of individual i minus the average return of cash-like WMPs in month t. $Max(RateGap\_Cash, X)_{i,t}$ equals the greater value of $RateGap\_Cash_{i,t}$ and X bps. $RateGap\_New_{i,t}$ is the mortgage rate of individual i minus the average benchmark return of newly-issued WMPs in month t. $Max(RateGap\_New, X)_{i,t}$ equals the greater value of $RateGap\_New_{i,t}$ and X bps. $RateGap\_Realized_{i,t}$ is the mortgage rate of individual i minus the average realized return of WMPs maturing in month t. $Max(RateGap\_Realized, X)_{i,t}$ equals the greater value of $RateGap\_Realized_{i,t}$ and X bps. Panel A presents the summary statistics of the interest rate gaps. In Panels B to E, the dependent variable is $Prepay_{i,t+1 \to t+6}$. Other variables are the same as those in Table 2. All variables are defined in Appendix A. We include city-time fixed effects. The sample is from October 2019 to December 2023. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: RateGap distribution

	N	Mean	P25	P50	P75
$RateGap$	3833523	0.30	-0.05	0.25	0.74
$RateGap\_Cash$	3833523	2.11	1.79	2.09	2.57
$RateGap\_New$	3833523	0.89	0.54	0.90	1.32
$RateGap\_Realized$	3833523	0.98	0.49	1.01	1.48

Panel B: RateGap based on LPR

	(1)	(2)	(3)	(4)	(5)
			$Prepay_{t+1 \to t+6}$		
X=	-0.6	-0.3	0	0.3	0.6
$Max(RateGap, X)$	0.01424***	0.01624***	0.01698***	0.01614***	0.01297***
	(17.22)	(17.09)	(17.04)	(17.23)	(15.18)
Controls	YES	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES	YES
R^2	0.5854%	0.5865%	0.5874%	0.5862%	0.5750%
N	3833523	3833523	3833523	3833523	3833523

Panel C: RateGap based on Newly Issued Rate Basis					
	(1)	(2)	(3)	(4)	(5)
			$Prepay_{t+1 \rightarrow t+6}$		
$X =$	0.4	0.7	1	1.3	1.6
$Max(RateGap\_New, X)$	0.01142***	0.01071***	0.00969***	0.00809***	0.00740***
	(16.93)	(17.78)	(18.44)	(14.61)	(15.90)
Controls	YES	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES	YES
R^2	0.5770%	0.5817%	0.5862%	0.5715%	0.5606%
N	3833523	3833523	3833523	3833523	3833523

Panel D: RateGap based on Realized Closed-Fund Rate					
	(1)	(2)	(3)	(4)	(5)
			$Prepay_{t+1 \rightarrow t+6}$		
$X =$	0.4	0.7	1	1.3	1.6
$Max(RateGap\_Realized, X)$	0.01219***	0.01106***	0.00961***	0.00828***	0.00771***
	(15.75)	(16.19)	(17.05)	(15.28)	(12.48)
Controls	YES	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES	YES
R^2	0.5798%	0.5814%	0.5809%	0.5768%	0.5701%
N	3833523	3833523	3833523	3833523	3833523

Panel E: RateGap based on rate for Cash-Like products					
	(1)	(2)	(3)	(4)	(5)
			$Prepay_{t+1 \rightarrow t+6}$		
$X =$	1.4	1.7	2	2.3	2.6
$Max(RateGap\_Cash, X)$	0.00509***	0.00506***	0.00539***	0.00482***	0.00463***
	(15.12)	(17.08)	(17.95)	(15.56)	(12.03)
Controls	YES	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES	YES
R^2	0.5548%	0.5634%	0.5817%	0.5743%	0.5668%
N	3833523	3833523	3833523	3833523	3833523

Table 4: Interest rate gaps, individual characteristics, and mortgage prepayments

This table presents the impacts of individual characteristics on the relationship between interest rate gaps and mortgage prepayments. The dependent variable, $Prepay_{i,t+1\rightarrow t+6}$, is a dummy variable which equals one if individual i prepays their mortgage between month $t+1$ to $t+6$, and zero otherwise. $Max(RateGap_{i,t}, 0)$ is the positive value for difference between the mortgage rate of individual i and the LPR in month t. $HighChar_{i,t}$ are binary indicators for high AUM, high education, and high credit scores in Columns (1) to (3), respectively. Specifically, $HighAUM_{i,t}$ equals one if individual i's AUM is above the 70th percentile of the sample, and zero otherwise. $HighEduc_i$ equals one if individual i has a degree higher than a bachelor's, and zero otherwise. $HighCredit_{i,t}$ equals one if individual i's credit score is above the 70th percentile of the sample, and zero otherwise. All control variables are the same as those in Table 2 and defined in Appendix A. We include ID fixed effects and city-time fixed effects. The sample is from October 2019 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
		$Prepay_{t+1 \rightarrow t+6}$	
Char	AUM	Education	CreditScore
*Max(RateGap, 0)*HighChar*	0.0165***	0.0183***	0.0138***
	(9.75)	(9.62)	(7.91)
HighChar	0.0224***	0.0190***	0.0170***
	(17.17)	(10.25)	(15.89)
Max(RateGap, 0)	0.0119***	0.0128***	0.0125***
	(16.06)	(17.91)	(15.91)
Controls	YES	YES	YES
City-Time FE	YES	YES	YES
Within R^2	0.63%	0.62%	0.59%
N	4391404	4391404	4391404

Table 5: Mortgage Prepayments and Household Savings and Consumption

This table examines the impacts of mortgage prepayments on individuals' savings and consumption. The dependent variables are defined as follows: $Log(Deposit)_{i,t}$ is the natural logarithm of individual i's total deposits in the commercial bank in month t; $Log(AUM)_{i,t}$ is the natural logarithm of individual i's AUM in month t; $Log(Consumption)_{i,t}$ is the natural logarithm of individual i's bank card consumption in month t. To be included in the sample, individuals must have at least one consumption record in each quarter during the sample period. $AfterPrePay_{i,t}$ is a dummy variable equal to one if individual i made at least one prepayment before month t, and zero otherwise. All control variables are the same as those in Table 2, except for Columns (1) and (2), individuals' AUM is excluded as a control. We include ID fixed effects and city-time fixed effects. The sample period is from October 2019 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Log(Deposit)	(2) Log(AUM)	(3) Log(Consumption)
AfterPrepay	-0.7793***	-0.7214***	-0.0206***
	(-116.49)	(-108.35)	(-2.65)
Controls	YES	YES	YES
ID FE	YES	YES	YES
City×Time FE	YES	YES	YES
Within R^2	0.69%	0.60%	0.17%
N	5344676	5344676	1026503

Table 6: Local Margin Reset and Prepayments

This table examines the impacts of a policy aimed at reducing local margins on mortgage prepayment behaviors. The dependent variable, $Prepay_{i,t}$, is a dummy variable which equals one if individual i prepays their mortgage in month t, and zero otherwise. $Treat_i$ equals one if individual i's local margin is lowered by the policy, and zero otherwise. $Post_t$ equals one if month t is after September 2023, and zero otherwise. Individual-level control variables include individual i's loan-to-value ratio and its quadratic term, credit score, log of total assets in the commercial bank and mortgage age dummies. All variables are defined in Appendix A. We include ID fixed effects and city-time fixed effects. The sample includes all mortgages in China's first tier cities (Beijing, Shanghai, Shenzhen, and Guangzhou). The sample period is from October 2022 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Prepay	
$Treat \times Post$	-0.005***	-0.005***
	(-5.68)	(-5.76)
Controls	NO	YES
ID FE	YES	YES
City-Time FE	YES	YES
Within R^2	0.011%	1.192%
N	13444263	13444263

Table 7: Local Margin Reset and Consumption

This table examines the impacts of a policy aimed at reducing local margins on household consumption. The dependent variable, $LogConsumption_{i,t}$, is the natural logarithm of individual i's bank card consumption in month t. $Treat_i$ equals one if individual i's local margin is lowered by the policy, and zero otherwise. $Post_t$ equals one if month t is after September 2023, and zero otherwise. Individual-level control variables include individual i's loan-to-value ratio and its quadratic term, credit score, log of total assets in the commercial bank and mortgage age dummies. All variables are defined in Appendix A. We include ID fixed effects and city-time fixed effects. The sample includes all mortgages in China's first tier cities (Beijing, Shanghai, Shenzhen, and Guangzhou). The sample period is from October 2022 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Log(Consumption)	
$Treat \times Post$	0.0067**	0.0068***
	(2.98)	(2.72)
Controls	NO	YES
ID FE	YES	YES
City-Time FE	YES	YES
Within R^2	0.000%	2.995%
N	5924701	5924701

Table 8: Interest rate gaps and mortgage prepayments at the city level

This table presents the effects of interest rate gaps on mortgage prepayments at the city level. In Panel A, the dependent variable, $PrepayCount_{c,t+1\to t+6}$, is the ratio of the number of mortgage prepayments to the total number of mortgage repayments of city c between month $t+1$ and month $t+6$. In Panel B, the dependent variable, $PrepayCount_{c,t+k}$, is the prepayment ratio of city c in month $t+k$, where k ranges from 1 to 6. $M\_City_{c,t}$ is the average interest rate of existing mortgages in city c for month t. $RateGap\_City_{c,t}$ is the difference between $M\_City_{c,t}$ and LPR_t. Control variables include PMI, the changes in CPI, GDP growth, GDP per capita, the average housing price, and the average change in housing price in city c for month t. We also include city fixed effects and year-month fixed effects. The sample is from October 2019 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Baseline

	(1)	(2)
	$PrepayCount_{t+1\to t+6}$	
RateGap_City	0.0042***	0.0040***
	(8.25)	(7.34)
Controls	NO	YES
City FE	YES	YES
Year-Month FE	YES	YES
Within R^2	3.19%	4.04%
N	12950	12950

Panel B: Dynamic

	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	t+2	t+3	t+4	t+5	t+6
RateGap_City	0.0040***	0.0044***	0.0044***	0.0031*	0.0043***	0.0053***
	(2.82)	(2.70)	(2.42)	(2.01)	(3.53)	(4.45)
Controls	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
R^2	1.08%	1.15%	1.08%	0.65%	0.92%	1.00%
N	12950	12680	12680	12420	12160	11900

Table 9: $Frac > 0$ and mortgage prepayments

In this table, we follow Berger et al., (2021) and use $Frac > X_{c,t-1}$ as the key independent variable. $Frac > X_{c,t-1}$ is the fraction of city c's existing mortgages with interest rates higher than $LPR + X$ in month $t-1$. We use five values for X: -60 bps, -30 bps, 0, 30 bps, and 60 bps. Control variables are the same of those in Table 8. We also include city fixed effects and year-month fixed effects. The sample is from October 2019 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time.

	(1)	(2)	(3)	(4)	(5)
			$PrepayCount_{t+1\rightarrow t+6}$		
X=	-60 bps	-30 bps	0 bps	30 bps	60 bps
$Frac > X$	0.0111***	0.0069***	0.0078***	0.0020***	0.0006
	(9.49)	(6.69)	(5.78)	(2.86)	(1.28)
Controls	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Within R^2	2.73%	3.30%	4.41%	1.76%	1.39%
N	12950	12950	12950	12950	12950

Table 10: Mortgage prepayments and consumption at the city level

This table presents the effects of mortgage prepayments on consumption growth at the city level. We follow Berger et al. (2021) and use $Frac > 0$ as the instrument variable for $PrepayCount$. Columns (1) and (2) present the results of the two stages of IV regressions. $\Delta Consumption_{c,t,t+6}$ is the average growth of consumption made through UnionPay cards in city c between months $t+1$ and $t+6$. $PrepayCount_{c,t}$ is the ratio of the number of mortgage prepayments to the total number of mortgage repayments of city c for month t. $Frac > 0_{c,t-1}$ is the fraction of existing mortgages with interest rates higher than the LPR in city c for month $t-1$. Control variables are consistent with those in Table 8. We also include city fixed effects and year-month fixed effects. Column (3) presents the results of the regression of consumption growth on prepayment ratios. The sample is from October 2019 to June 2023. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	IV		OLS
	$PrepayCount_t$	$\Delta Consumption_{t+1\to t+6}$	$\Delta Consumption_{t+1\to t+6}$
$Frac{>}0_{t-1}$	0.0137***		
	(5.32)		
$PrepayCount_t$		-31.9645***	-20.0648***
		(-4.70)	(-5.30)
F-Stat	28.30		
Controls	YES	YES	YES
City FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Within R^2	3.37%	0.58%	4.30%
N	6426	6426	6426

Table 11: Mortgage prepayments and different types of consumption at the city level

This table presents the effects of mortgage prepayments on different types of consumption growth at the city level. We follow Berger et al., (2021) and use $Frac > 0$ as the instrument variable for $PrepayCount$. In Panel A, $\Delta ConsumptionEssn_{c,t+1\rightarrow t+6}$ ($\Delta ConsumptionDisc_{c,t+1\rightarrow t+6}$) is the average growth of essential (discretionary) consumptions in city c between months $t+1$ and $t+6$. We report the results of the two stages of IV regressions in Columns (1) and (3), and the results of OLS regressions in Columns (2) and (4), respectively. In Panel B, $\Delta ConsumptionS_{c,t+1\rightarrow t+6}$ ($\Delta ConsumptionL_{c,t+1\rightarrow t+6}$) is the average growth of small (large) consumptions in city c between months $t+1$ and $t+6$. Small (Large) consumptions in a city for a month are the sum of the consumptions with values lower (higher) than 1,000 RMB in that city for the month. Control variables are consistent with those in Table 8. We also include city fixed effects and year-month fixed effects. The sample is from October 2019 to June 2023. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Mortgage prepayment and essential vs discretionary consumption

	(1)	(2)	(3)	(4)
	$\Delta ConsumptionEssn_{t+1\rightarrow t+6}$		$\Delta ConsumptionDisc_{t+1\rightarrow t+6}$	
	IV	OLS	IV	OLS
$PrepayCount_t$	-11.4664	-5.2163**	-45.9138***	-14.2855***
	(-1.17)	(-2.18)	(-4.16)	(-3.79)
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
R^2	0.27%	0.46%	0.518%	1.564%
N	6426	6426	6426	6426

Panel B: Mortgage prepayment and small vs large consumption

	(1)	(2)	(3)	(4)
	$\Delta ConsumptionS_{t+1\rightarrow t+6}$		$\Delta ConsumptionL_{t+1\rightarrow t+6}$	
	IV	OLS	IV	OLS
$PrepayCount_t$	-6.1824	-10.1778***	-31.5907***	-19.5750***
	(-0.99)	(-4.47)	(-4.66)	(-5.18)
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Within R^2	0.42%	1.66%	0.57%	4.13%
N	6426	6426	6426	6426

Table 12: Changes in LPR, $Frac > 0$, and consumption growth

This table presents the impacts of mortgage prepayment on the relationship between changes in LPR and consumption growth at the city level. The dependent variable, $\Delta Consumption_{c,t,t+6}$, is the average growth of consumption made through UnionPay cards in city c between months $t+1$ and $t+6$. $Frac > 0_{c,t-1}$ is the fraction of existing mortgages with interest rates higher than the LPR in city c for month $t-1$. $HighFrac_{c,t-1}$ is a dummy variable that takes the value one if $Frac > 0_{c,t-1}$ is above the 70th percentile of the sample, and zero otherwise. ΔLPR_t is the change in LPR from month $t-1$ to month t. Control variables are consistent with those in Table 8. We also include city fixed effects and year-month fixed effects. The sample is from October 2019 to June 2023. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively.

	$\Delta Consumption_{t+1,t+6}$
$HighFrac_{t-1} * \Delta LPR_t$	0.4104**
	(2.34)
Controls	YES
City FE	YES
Year-Month FE	YES
Within R^2	0.40%
N	6426

Table 13: Mortgage prepayments and lending at the city level

This table presents the effects of mortgage prepayments on lending growth at the city level. The dependent variable, $\Delta Lending_{c,t,t+6}$, is the average growth of lending provided by financial institutions in city c between months $t+1$ and $t+6$. $PrepayCount_{c,t}$ is the ratio of the number of mortgage prepayments to the total number of mortgage repayments of city c for month t. $Frac > 0_{c,t-1}$ is the fraction of existing mortgages with interest rates higher than the LPR in city c for month $t-1$. We follow Berger et al. (2021) and use $Frac > 0$ as the instrument variable for $PrepayCount$. Control variables are consistent with those in Table 8. We report the result of two stages of IV regressions in Columns (1) and (2), and the OLS results in Column (3). We also include city fixed effects and year-month fixed effects. The sample is from October 2019 to June 2023. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	IV		OLS
	$PrepayCount_t$	$\Delta Lending_{t+1\to t+6}$	$\Delta Lending_{t+1\to t+6}$
$Frac{>}0_{t-1}$	0.0126***		
	(3.52)		
$PrepayCount_t$		-1.1934***	-0.0482***
		(-5.01)	(-3.18)
F-Stat	12.39		
Controls	YES	YES	YES
City FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Within R^2	0.98%	0.57%	0.54%
N	6368	6368	6368

Appendix A. Variables Definition

Variable	Definition
Individual-level variables	
$Prepay_{i,t+1+6}$	A dummy variable which equals one if individual i prepays their mortgage between month $t+1$ to $t+6$, and zero otherwise.
$m_{i,t}$	The mortgage rate for individual i in month t.
$RateGap_{i,t}$	The difference between the mortgage rate of individual i and the loan prime rate (LPR) in month t.
$LogDeposit_{i,t}$	The natural logarithm of the deposit of individual i at the commercial bank in month t.
$LogAUM_{i,t}$	The natural logarithm of the AUM of individual i at the commercial bank in month t.
$Age_{i,t}$	The age of the individual i in month t.
$HighEduc_{i,t}$	A dummy variable which equals one if individual i has a degree higher than a bachelor's and zero otherwise.
$Male_{i,t}$	A dummy variable which equals one if individual i is a male and zero otherwise.
$Score$	The internal credit score of individual i in month t.
LTV	The ratio of mortgage balance to housing value.
$LogBalance$	The natural logarithm of remaining mortgage balance for individual i in month t.
City-level variables	
$PrepayCount_{c,t}$	The ratio of the number of mortgage prepayments to the total number of mortgage repayments in city c for month t.
$PrepayValue_{c,t}$	The ratio of the value of mortgage prepayments to the total value of mortgage payments in city c for month t.

Variable	Definition
$M\_City_{c,t}$	The average interest rate of existing mortgages in city c for month t.
LPR_t	The LPR rate in month t.
$RateGap\_City_{c,t}$	M_City - LPR
$RateGap\_CityAlt_{c,t}$	M_City - LocalNewRate
$Frac > 0_{c,t}$	The fraction of existing mortgages with interest rates higher than LPR in city c for month t.
$\Delta Consumption_{c,t+1\to t+6}$	The average growth of consumption made through UnionPay cards in city c between from $t+1$ to $t+6$
$\Delta ConsumptionDisc_{c,t+1\to t+6}$	The average growth of discretionary consumption made through UnionPay cards in city c between from $t+1$ to $t+6$. The discretionary categories include alcohol, tobacco, car, electronic devices, entertainment, and inter-city transportation.
$\Delta ConsumptionEssn_{c,t+1\to t+6}$	The average growth of essential consumption made through UnionPay cards in city c between from $t+1$ to $t+6$. The essential categories include food, gasoline, utilities, household and telephone services.
$\Delta ConsumptionS_{c,t+1\to t+6}$	The average of growth of small consumptions in city c between month $t+1$ and $t+6$. Small consumptions in a city for a month are the sum of the consumptions with values lower than 1,000 RMB in that city for the month.
$\Delta ConsumptionL_{c,t+1\to t+6}$	The average of growth of large consumptions in city c between month $t+1$ and $t+6$. Large consumptions in a city for a month are the sum of the consumptions with values higher than 1,000 RMB in that city for the month.
$\Delta Lending_{c,t,t+6}$	The average growth of lending from financial institutions in city c between from $t+1$ to $t+6$.

Variable	Definition
$GDPGrowth_{c,t}$	Yearly real GDP growth rate.
$GDPPerCap_{c,t}$	The natural logarithm of GDP per capita.
CPI_t	The change of the Consumer Price Index in the prior month.
PMI_t	The Purchasing Managers' Index for the prior month.
$LogHousingPrice_{c,t}$	The natural logarithm of average housing price in city c for month t. Price is computed using housing appraisal value and housing area recorded in mortgage database.
$\Delta HousingPrice_{c,t}$	The log change of housing price in city c for month t.

Appendix B. Additional Empirical Results

Table A1: Savings rates and LPR

This table reports how rates of various wealth management products vary with the LPR. Savings rates include the average return of the cash-like WMPs ($Cash$), the average benchmark return of newly issued WMPs (New), the average realized return of WMPs maturing in current quarter (*Realized*). We also include average rate basis for newly issued products and realized rate for closed-fund products with more than three years duration (New_3Y and *Realized_3Y*, respectively). We regress these rates on 5 year LPR Rate (LPR) and present the results in Panel A. Panel B reports the differences between the benchmark returns at the end of the sample period and those at the beginning. The data spans from 2019Q4 to 2023Q4, except for *Realized_3Y* which spans from 2020Q2 to 2023Q4 with missing. The t-statistics in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with 12 lags. $***$, $**$ and $*$ denote significance at the 1%, 5% and 10% levels.

Panel A: LPR and savings rates

	$Cash$	New	*Realized*	New_3Y	*Realized_3Y*
LPR	1.417***	1.068***	2.473***	1.780**	1.357***
	(13.45)	(7.41)	(6.63)	(2.49)	(3.55)
Constant	-0.037	-0.009	-0.074	-0.029	-0.007
	(-7.78)	(-1.38)	(-4.37)	(-0.90)	(-0.41)
N	17	17	17	17	6
R-squared	0.923	0.785	0.746	0.292	0.759

Panel B: Changes in rates from the beginning to the end of the sample

	ΔLPR	$\Delta Cash$	ΔNew	Δ*Realized*	ΔNew_3Y
2023Q4 - 2019Q4	-0.600%	-0.744%	-0.720%	-0.955%	-1.825%
	ΔLPR	Δ*Realized_3Y*			
2023Q4 - 2020Q2	-0.450%	-0.579%			

Table A2: Interest rate gap and mortgage prepayments, robustness

This table presents the effects of interest rate gaps on mortgage prepayments at the loan level. In Panel A, the dependent variable is the prepayment dummy for a specific month $t+k$, where k ranges from 1 to 6. In Panel B, the dependent variable is $Prepay_{i,t+1\rightarrow t+6}$, a binary indicator equal to one if individual i prepays their mortgage between months $t+1$ and $t+6$, and zero otherwise. The key independent variable $RateGap_{i,t}$ is the mortgage rate of individual i minus the LPR in month t. Individual-level control variables include individual i's loan-to-value ratio and its quadratic term, credit score, log of total assets in the commercial bank, mortgage age dummies, dummies for high education and gender. Macro-level control variables include the GDP growth rate, GDP Per capita, the average price of new houses, and the average change in the housing prices in individual i's city in month t. All variables are defined in Appendix A. In Panel A, we include city-time fixed effects. In Panel B, we additionally control for ID fixed effects to generate a within-ID estimator. The sample is from October 2019 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Dynamic

	(1)	(2)	(3)	(4)	(5)	(6)
Prepay	t+1	t+2	t+3	t+4	t+5	t+6
RateGap	0.0018***	0.0017***	0.0018***	0.0017***	0.0018***	0.0017***
	(8.59)	(8.51)	(8.89)	(9.23)	(9.37)	(9.29)
Controls	YES	YES	YES	YES	YES	YES
City-Time FE	YES	YES	YES	YES	YES	YES
Within R^2	0.27%	0.10%	0.10%	0.51%	0.07%	0.07%
N	4386518	4391404	4391404	4386518	3970810	3870227

Panel B: Control for individual fixed effects

	(1)	(2)	(3)
		$Prepay_{t+1\rightarrow t+6}$	
RateGap	0.0064***	0.0050**	0.0062***
	(2.91)	(2.12)	(2.58)
Controls	NO	YES	YES
ID FE	YES	YES	YES
Year-Month FE	YES	YES	N.A.
City-Time FE	NO	NO	YES
Within R^2	0.00%	0.59%	0.68%
N	4391403	4386470	4386470

Table A3: Treatment intensity and mortgage prepayments

This table examines the impacts of a policy aimed at reducing local margins on mortgage prepayment behaviors. The dependent variable, $Prepay_{i,t}$, is a dummy variable which equals one if individual i prepays their mortgage in month t, and zero otherwise. *ReducedRate* is the absolute value of reduced rates due to the policy. $Post_t$ equals one if month t is after September 2023, and zero otherwise. Individual-level control variables include individual i's loan-to-value ratio and its quadratic term, credit score, log of total assets in the commercial bank and mortgage age dummies. All variables are defined in Appendix A. We include ID fixed effects and city-time fixed effects. The sample includes all mortgages in China's first tier cities (Beijing, Shanghai, Shenzhen, and Guangzhou). The sample period is from October 2022 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Prepay	
$ReducedRate \times Post$	-0.009***	-0.009***
	(-4.81)	(-5.02)
Controls	NO	YES
ID FE	YES	YES
City×Time FE	YES	YES
Obs	13,444,263	13,444,263
Within R^2	0.01%	1.19%

Table A4: Effect of Treatment on heterogeneous Prepayments

This table examines the impacts of a policy aimed at reducing local margins on partial and full prepayment behaviors. The dependent variable includes, $PartialPrepay_{i,t}$, a dummy variable which equals one if individual i partially prepays his or her mortgage in month t, and zero otherwise; and $FullPrepay_{i,t}$, a dummy variable which equals one if individual i fully prepays his or her mortgage in month t, and zero otherwise. $Treat$ equals one if the household are affected by the policy, and zero otherwise. $Post_t$ equals one if month t is after September 2023, and zero otherwise. Individual-level control variables include individual i's loan-to-value ratio and its quadratic term, credit score, log of total assets in the commercial bank and mortgage age dummies. All variables are defined in Appendix A. We include ID fixed effects and city-time fixed effects. The sample includes all mortgages in China's first tier cities (Beijing, Shanghai, Shenzhen, and Guangzhou). The sample period is from October 2022 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Partial Prepay		*Full Prepay*	
	(1)	(2)	(3)	(4)
$Treat \times Post$	-0.003***	-0.004***	-0.001***	-0.001**
	(-2.85)	(-3.88)	(-3.17)	(-2.05)
Controls	NO	YES	NO	YES
ID FE	YES	YES	YES	YES
City×Time FE	YES	YES	YES	YES
Obs	13,444,263	13,444,263	13,444,263	13,444,263
Within R^2	0.011%	0.494%	0.002%	0.967%

Table A5: Interest rate gaps and mortgage prepayments at the city level, robustness tests

This table presents the robustness tests of the effects of interest rate gaps on mortgage prepayments at the city level. The dependent variable, $PrepayValue_{c,t+1\to t+6}$, is the ratio of the mortgage prepayments value to the total value of mortgage repayments of city c between month $t+1$ and month $t+6$. $RateGap\_CityAlt_{c,t}$ is the difference between $M\_City_{c,t}$ and $LocalNewRate_{c,t}$. Control variables are the same of those in Table 8. We also include city fixed effect and year-month fixed effect. The sample is from October 2019 to May 2024. The t-statistics, shown in parentheses, are calculated using standard errors clustered by time. $***$, $**$, and $*$ indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Replace the number of prepayments with the value of prepayments		
	$PrepayValue_{t+1\to t+6}$	
RateGap_City	0.1019***	0.0955***
	(8.57)	(7.78)
Controls	NO	YES
City FE	YES	YES
Year-Month FE	YES	YES
Within R^2	3.63%	4.16%
N	12950	12950

Appendix C. Model

C.1. Model Setup

Consider a household that lives for three periods $t = 0, 1$ and 2, but Consumes only at $t = 1$ and 2. Preferences over consumption of household i at $t = 1, 2$ are

$$ln(c_{i,1}) + ln(c_{i,2})$$

In period 0, household i purchases a house with a mortgage and needs to pay back in the last two periods. The mortgage rate is m_i. The total amount of the mortgage if paid in period 2 is M_i. If she decides to prepay a proportion of p, she needs to prepay $\frac{M_i p_i}{1+m_i}$ in period 1 and repay $M_i(1 - p_i)$ in period 2. Households receive income $w_{i,1}$ in period 1 and make their consumption, saving, and prepayment (if any) decisions in period 1. In period 2, households receive income $w_{i,2}$, pay back the rest of their mortgages, and consume. As such, households maximize their utility by making mortgage (pre) payments, saving, and consumption decisions. Note that for simplicity, there is no uncertainty because the income path $(w_{i,1}, w_{i,2})$ is known at $t = 0$. Assume there is no default.

Note that households could save at the rate r but they cannot borrow with this rate because of refinance constraints.

Additionally, as there is no default on mortgage payments, we assume their life-time income can afford the mortgage payment, i.e.,

$$w_{i,1}(1 + r) + w_{i,2} > M_i.$$

We also assume that income in either period alone can not afford the mortgage payment, thus

$$w_{i,1}(1 + r) < M_i$$

$$w_{i,2} < M_i$$

The optimization decision for household i is specified as follows

$$\max_{p_i, c_{i,1}} ln(c_{i,1}) + ln(c_{i,2})$$

s.t.

$$(w_{i,1} - \frac{M_i p_i}{1+m_i} - c_{i,1})(1+r) + w_{i,2} - M_i(1-p_i) = c_{i,2}$$

$$0 \leq p_i \leq 1$$

$$w_1 - \frac{M_i p}{1+m_i} - c_{i,1} \geq 0$$

C.2. Solutions

Because mortgage prepayment could be considered a means of savings at the rate m_i, then we have

- If $m_i > r$, prepayment dominates savings and households prepay the mortgage as much as they can. As a result,

$$c_{i,1} = w_{i,1} - \frac{M_i p_i}{1+m_i}$$

$$c_{i,2} = w_{i,2} - M_i(1-p_i)$$

Based on F.O.C. with respect to p_i, if the constraints on p_i are not binding, we have

$$p_i = \frac{w_{i,1}(1+m_i) - w_{i,2} + M_i}{2M_i}, \tag{1}$$

and

$$c_{i,1} = \frac{w_{i,1}(1+m_i) + w_{i,2} - M_i}{2(1+m_i)},$$

$$c_{i,2} = \frac{w_{i,1}(1+m_i) + w_{i,2} - M_i}{2},$$

if

$$w_{i,1}(1+m_i) - w_{i,2} \leq M_i.$$

When

$$w_{i,1}(1+m_i) - w_{i,2} > M_i,$$

$p_i = 1$, the household fully prepays the mortgage. Then based on F.O.C. with respect to $c_{i,1}$, we have

$$c_{i,1} = \frac{w_{i,1}(1+r) + w_{i,2} - \dfrac{M_i(1+r)}{1+m_i}}{2(1+r)}$$

$$c_{i,2} = \frac{w_{i,1}(1+r) + w_{i,2} - \dfrac{M_i(1+r)}{1+m_i}}{2}$$

- If $m_i \leq r$, saving dominates the mortgage prepayment and households do not prepay their mortgages. As a result, $p_i = 0$. The borrowing constraint is not binding. Based on F.O.C. with respect to $c_{i,1}$, we have

$$c_{i,1} = \frac{w_{i,1}(1+r) + w_{i,2} - M_i}{2(1+r)}$$

$$c_{i,2} = \frac{w_{i,1}(1+r) + w_{i,2} - M_i}{2}$$

if

$$w_{i,2} - M_i \leq w_{i,1}(1+r).$$

Otherwise,

$$c_{i,1} = w_{i,1}$$

$$c_{i,2} = w_{i,2} - M_i.$$

However, this case would not happen given the assumption that $w_{i,2} < M_i$

C.3. Discussions

First, from the equation 1, conditional on prepayment, the proportion of prepayment p_i increases with the mortgage rate m_i and income $w_{i,1}$.

Second, when the saving rate r decreases from r_a to r_b ($r_a > r_b$), households with m_i between r_b and r_a choose to prepay their mortgages. Because we assume that income in either period alone can not afford the mortgage payment, i.e.,

$$w_{i,1}(1+r_a) < M_i,$$

we only consider consumption when $p_i < 1$. Therefore, before the change in the saving rate,

$$c_{i,1}^a = \frac{w_{i,1}(1+r_a) + w_{i,2} - M_i}{2(1+r_a)},$$

$$c_{i,2}^a = \frac{w_{i,1}(1+r_a) + w_{i,2} - M_i}{2}.$$

After the change,

$$c_{i,1}^b = \frac{w_{i,1}(1+m_i) + w_{i,2} - M_i}{2(1+m_i)},$$

$$c_{i,2}^b = \frac{w_{i,1}(1+m_i) + w_{i,2} - M_i}{2},$$

Since income in period 2 cannot afford the full mortgage payment, i.e., $w_{i,2} < M_i$, we have $c_{i,1}^b < c_{i,1}^a$ and $c_{i,2}^b < c_{i,2}^a$. Consumption decreases after the reduction in the saving rate.