Rigid Mortgage Rates and Monetary Policy Transmission^{*}

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Abstract

During the 2019–2024 monetary easing cycle, Chinese households used their savings to prepay unprecedented amounts of mortgage loans. Mortgage rates remained rigid due to banks' market power and refinancing restrictions, while savings returns quickly adjusted to rate cuts. The widening gap between borrowing and savings returns encouraged deleveraging and reduced consumption. Exploiting loan-level data from a major bank, a quasi-natural policy experiment, and UnionPay's spending records, we provide household- and city-level evidence that larger positive gaps between mortgage rates and the benchmark rate drive greater prepayments and lower consumption. Our findings suggest that mortgage rate rigidity could make monetary easing counterproductive.

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1. Introduction

In response to the economic slowdown, China's central bank began cutting interest rates in 2019 to stimulate lending and revive the economy. However, this policy triggered an unintended consequence: a surge in households' mortgage prepayments, primarily funded by savings without refinancing, as suggested by anecdotal evidence.¹ This implied households' voluntary deleveraging rather than increased borrowing—contrary to the intended goal of expansionary monetary policy. The total amount of mortgage prepayments is massive: Market estimates indicate that total mortgage prepayments in 2022 reached 4.7 trillion yuan (700 billion USD), or 12% of total outstanding mortgage loans, a trend that persisted into the first half of $2024.^2$

Such an unprecedented and puzzling episode makes regulators and scholars wonder what motivates households to prepay their mortgages (deleveraging) following a rate cut. More importantly, what are the macroeconomic consequences of this massive wave of prepayments and implications to monetary policy transmission? In this paper, we answer these questions by analyzing loan-level data from one of China's major banks. Our findings provide new insights into how interest rate pass-through functions in the household sector, with a mechanism that highlights the role of mortgage rate rigidity and can be generalized to other markets where rate pass-through to mortgage debts is limited.

Between 2019 and 2024, the People's Bank of China (PBOC) repeatedly reduced borrowing costs, lowering the 5-year Loan Prime Rate (LPR)—the benchmark for mortgage loans—from 4.85% in October 2019 to 3.95% by May 2024. However, Chinese households derived limited benefits from these reductions due to institutional frictions. First, while most mortgage loans in China have floating rates, these rates adjust only partially to the benchmark rate and often with significant delays (as detailed later). Second, mortgage refinancing is highly limited for Chinese households because of regulatory restrictions. These frictions, driven largely by the market power of state-owned banks and their influence on regulatory

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

²Liu 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 (PBOC), 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.

policymaking, make mortgage rates downwardly rigid in response to monetary easing.³ As a result, the average rate of existing mortgages stayed significantly higher than the LPR, with the gap increasing from 0.12% in October 2019 to the highest 0.57% in 2022 before narrowing after PBOC's intervention in September 2023.

Chinese households often hold substantial savings in wealth management products (WMPs), which are liquid and offer higher returns than traditional deposits. WMPs primarily invest in short-term bonds and money market instruments, and their returns adjust quickly—and often amplify—in response to benchmark rate cuts.⁴ This creates an asymmetric rate pass-through on household balance sheets: while mortgage rates remain rigid, WMP returns fall rapidly. The gap between average mortgage rates and WMP returns grew from 0.75% in 2019–2020 to 1.90% in early 2023. When the rate gap is small, households tend to accept it as a premium for maintaining precautionary liquidity. However, as the gap widens, households shift their optimal choices by reducing borrowing and prepaying mortgages. This deleveraging, in turn, leads to a contraction in household consumption.

This mechanism weakens monetary policy transmission, as rate cuts reduce, rather than increase, household borrowing and consumption. The key friction lies in the downward rigidity of mortgage rates, which causes an asymmetric pass-through of interest rates on household balance sheets. China's unique regulatory environment, where mortgage refinancing is highly restricted, provides an ideal setting to identify this mechanism. However, similar rigidities can also occur in other markets due to banks' market power (Scharfstein and Sunderam (2016)) and refinancing frictions (Agarwal, Rosen, and Yao (2016); Andersen, Campbell, Nielsen, and Ramadorai (2020); Keys, Pope, and Pope (2016)). In this sense, our findings are broadly relevant and shed light on how mortgage markets shape monetary policy transmission.

We test the proposed mechanisms using loan-level data from one of the major stateowned banks (the bank, hereafter) in China from October 2019 to May 2024. This bank has branches all over the country with a large share of the mortgage market. 37.5% of the

³The six major state-owned banks collectively account for 77% of the market share, with the top two banks alone controlling over half of China's residential mortgage market in 2024, according to the statistics from WIND (https://www.yicai.com/news/102255195.html).

⁴The amplification effect is consistent with the credit channel and risk-taking channel of monetary policy transmission in literature (e.g., Bauer, Bernanke, and Milstein (2023); Bernanke and Gertler (1995)).

borrowers in our sample have made at least one prepayment during the sample period. A significant portion of prepayments are partial, consistent with the anecdote that Chinese households use savings to prepay mortgages rather than refinance them.

We begin by analyzing the motives behind mortgage prepayments. Our hypothesis suggests that the primary driver of household mortgage prepayment is the rate gap between the current mortgage rate and the returns on household savings. The mortgage rate is typically set as the LPR plus a fixed local margin in China. While the LPR is a floating component, it adjusts only annually. The local margin, set at the time of loan issuance, remains fixed throughout the loan term and is determined by city-level home purchase policies. Thus, this margin varies significantly across cities and over time, and within city and time, it also depends on borrowers' home portfolios.⁵ Household returns on WMPs or bank deposits are not directly observed in our dataset, and the availability of investment options may differ across households. Therefore, we use the LPR as the primary proxy and also consider using average returns on WMPs as alternatives in our empirical analysis (more on this later). The interest rate gap, denoted as *RateGap*, is calculated as the household's current mortgage rate minus the LPR. Given that the adjustment of mortgage rate to LPR is partial and delayed, *RateGap* will rise as the LPR decreases.⁶

We test whether borrowers are more likely to prepay as the rate gap increases. A key identification challenge is that changes in interest rates may reflect broader economic conditions that influence household decisions. For instance, economic downturns or households' pessimistic expectations may drive deleveraging through prepayments, with rate cuts being a consequence of such conditions rather than the primary driver. To address this issue, we include year-month fixed effects to control for macroeconomic factors and, in some specifications, city-by-time fixed effects to account for regional variation in economic conditions. Additionally, we control for borrower-specific characteristics (e.g., leverage ratio, credit score, and total assets) and local economic variables (e.g., GDP growth, housing price changes, and inflation).

More importantly, to further strengthen the identification, we exploit the non-linear ef-

⁵See more details in Section 2.

 $^{^6\}mathrm{This}$ effect is even more pronounced for the approximately 10% of mortgages in our sample that are fixed-rate loans.

fect of the rate gap on prepayment propensity. That is, as the LPR decreases, borrowers are more likely to prepay only when RateGap exceeds a certain threshold, while the effect is insignificant when RateGap is small or negative. This test leverages the loan-level heterogeneity in current mortgage rates (within city by time), which arises from differences in the fixed component (the local margin) of the mortgage rate and the timing of adjustments to the LPR. Since both the local margin and adjustment schedule are determined at the time of mortgage issuance, the premise of our empirical strategy is that the distance between a borrower's RateGap and the threshold is uncorrelated with households' current exposure to and expectations of macroeconomic conditions.

In our baseline regression, we use Max(RateGap, 0), where 0 serves as the threshold. Our findings uncover a significant and convex relationship between RateGap and prepayment behavior. In terms of economic magnitude, a 50-basis-point increase in RateGap in the positive regime raises the likelihood of prepayment within six months by 0.86%, which is meaningful given the average six-month prepayment likelihood of 6.3% during the sample period. The findings are robust to using alternative proxies for savings returns, such as WMP returns, and other threshold values.⁷

This non-linear pattern bears some resemblance to findings in the US mortgage market. For instance, Berger, Milbradt, Tourre, and Vavra (2021) show that the gap between existing and new mortgage rates can trigger significant prepayment activity, with the effect exhibiting a step-like function around zero. However, we argue that the patterns observed in China differ in several important ways due to its distinct underlying mechanism.

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 limited. Our results confirm that the effect is more pronounced for borrowers with higher wealth, education, and credit scores. 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

⁷The baseline specification of our analysis uses the LPR with a threshold value of zero, as this specification provides the best fit to the data based on R^2 . For details, see Section 4.2.

to reduce interest expenses (Berger et al., 2021). Third, consistent with our hypothesis, prepaying households in China experience a substantial and sustained decline in their long-term savings levels. This again contrasts with the U.S., where prepayment behavior is often associated with refinancing rather than drawing down savings.

We next examine households' consumption patterns before and after mortgage prepayment. To formalize the intuition, we develop a stylized model in Appendix B 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, we find consistent empirical evidence: households that prepaid their mortgages tend to reduce their consumption by 2.06% afterward. This finding highlights a potentially counterproductive effect of monetary policy through the mortgage prepayment channel: in the presence of mortgage rate rigidity, cutting benchmark rates could inadvertently lead to a reduction in household consumption.

We further exploit a quasi-natural policy experiment to provide causal evidence. On August 31, 2023, the PBOC, in collaboration with local governments, announced a new policy allowing certain borrowers to reset the local margin of their existing mortgage loans to the lower first-home margin, even if they were not classified as first-home borrowers at the time of purchase. The policy's key element was redefining the "first home" criteria. One-quarter of the households in our sample qualified, with their mortgage rates reduced by an average of 50 basis points. In aggregate, we find the average *RateGap* fell to around zero after the intervention, aligning with the PBOC's policy objective of breaking mortgage rate rigidity.

Using a difference-in-difference design, we find that treated households were less likely to prepay their mortgages after the policy change and tended to increase consumption relative to the control group.⁸ The results suggest that a policy intervention enabling interest rate adjustments to pass through to mortgage loans can effectively reduce mortgage prepayments

 $^{^{8}}$ We also confirm the parallel trends of prepayment and consumption between the treatment and control groups before the policy shock; see Figure 5.

and stimulate household consumption.

In the second part of our analysis, we explore the implications of mortgage prepayment behavior for monetary policy transmission. At the loan level, rigid mortgage rates and rate gaps lead to deleveraging and lower consumption during PBOC rate cuts. We further analyze the macroeconomic impact on city-level aggregate consumption. A key challenge in this analysis is identifying the causal effect of interest rate cuts on total consumption growth 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 prepayment channel we focus on. Our objective is to identify the causal effect of LPR adjustments on household consumption through prepayments.

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 impact on mortgage prepayment varies substantially across cities. This variation depends on the city's average mortgage loan rates, which reflects the path of each city's historical policies on home purchases, local margin rate and LPR adjustment schedules, and the timing of residents' home purchase waves. 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 further strengthens the identification power of our tests. In sum, our empirical premise is that, given this path-dependent nature, Frac > 0 is plausibly uncorrelated with current city-level economic conditions affecting prepayment behavior, after controlling for time and city fixed effects as well as other relevant macroeconomic variables.

Specifically, we aggregate individual prepayment behavior by city and calculate *Prepay-Count*, the fraction of mortgage borrowers in a city who prepay over the subsequent 6 months. We then use Frac > 0 at the city level as an instrumental variable (IV) for *PrepayCount*. The *F*-statistic of the first-stage regression is 28.3, eliminating the concern about weak IV. In the second-stage regression, we use the instrumented *PrepayCount* to predict subsequent growth in total consumption. City-level aggregate consumption is meansured with the total spending through UnionPay bank cards.⁹ 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 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 5.09% decrease in aggregate consumption growth rate. 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, interest rate cuts are less likely—or even counterproductive—in stimulating household borrowing and consumption.

Second, our event study, based on the 2023 policy intervention, highlights the necessity and effectiveness of unconventional monetary measures. Policies that directly adjust mortgage rates can effectively address frictions in rate pass-through and mitigate mortgage rate rigidity.¹⁰ As another policy initiative, the PBOC introduced a new mortgage rate pricing scheme on September 29, 2024. The scheme allows local margins to adjust to market conditions and shortens LPR adjustment periods from one year to as little as one quarter.¹¹ The 2024 policy intervention, which aimed to further enhance monetary policy transmission through the household channel, are consistent with the proposed mechanism and findings of our paper.

Ultimately, allowing household mortgage rates to fully float with the central bank's benchmark rate is essential. Such an arrangement would enhance monetary policy transmission by ensuring that reductions in benchmark rates are quickly reflected in household borrowing

⁹The 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.

¹⁰Our findings align with Agarwal, Deng, Gu, He, Qian, and Ren (2022), who document how a similar policy during the 2008 financial crisis in China, mandating immediate reductions in benchmark lending rates for all existing mortgages, led to measurable increases in household consumption.

¹¹For details, see http://www.pbc.gov.cn/en/3688110/3688172/5188125/5472372/index.html.

costs. This would boost consumption and improve the effectiveness of monetary policy in achieving its macroeconomic objectives.

Literature Review First, the paper's main hypothesis builds on the previous studies on bank market power and various frictions and limitations of mortgage refinancing. Drechsler, Savov, and Schnabl (2017) illustrate that deposit rates do not rise significantly after monetary tightening due to banks' market power. Scharfstein and Sunderam (2016) find that mortgage rates fall less in response to monetary easing in concentrated markets, and Wang, Whited, Wu, and Xiao (2022) quantify these effects through a structural model. For the studies on mortgage refinancing, 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 et al. (2016); Bhutta and Keys (2016); Keys et al. (2016); Andersen et al. (2020)). The observed rigidity of mortgage rates in China is a consequence of the strong market power of state-owned banks and regulatory restrictions on refinancing. Our paper contributes to the literature by offering new insights into how rigid mortgage rates could lead to counter-productive consequences of expansionary monetary policies through mortgage prepayments (deleveraging).

Second, 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)). In particular, our paper is connected to two studies that investigate the distribution of mortgage rates to generate state-dependent prepayment decisions, Berger et al. (2021) and Eichenbaum, Rebelo, and Wong (2022). While our study confirms that households' decisions to prepay mortgages are influenced by the historical pattern of interest rates and the distribution of mortgage rates—making them path- and state-dependent, as noted in previous studies the motives for mortgage prepayment in China and its macroeconomic consequences differ entirely from the findings in the U.S., as discussed earlier.

Related, previous research on mortgage prepayment has predominantly focused on the U.S. 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 U.K., Bajo and Barbi (2018) investigating Italy, and Andersen et al. (2020) exploring Denmark, the literature on mortgage prepayment in non-U.S. markets remains relatively limited and has little coverage on emerging markets. Our paper adds evidence from the largest emerging market and highlights the role of market frictions (e.g., refinancing restriction) in shaping household behavior and policy outcomes, with a mechanism that is less obvious to identify in developed markets.

Third, we add 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 Kaplan and Violante (2014), Kaplan, Violante, and Weidner (2014), Agarwal, Green, Rosenblatt, and Yao (2015), Di Maggio, Kermani, and Palmer (2016), 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. We also emphasize the important role of the mortgage market but propose a novel mechanism, which builds on the asymmetric rate pass-through on the two sides of households' balance sheet. Our analysis shows that the aggregate effects of monetary easing can be significantly weakened, or even counterproductive, through this mechanism.

Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao (2017) also highlight the importance of household balance sheets and mortgage contract rigidity in monetary policy transmission. They show that reductions in mortgage rates due to resets of adjustable-rate mortgages (ARMs) lead to increased car purchases, but this effect is attenuated when borrowers choose prepay mortgages with saved interest expenses (voluntary deleveraging). We demonstrate a different mechanism: in the presence of strong mortgage rate rigidity, central bank rate cuts can trigger voluntary deleveraging and consumption contraction, without lowering borrowers' interest costs.

Fourth, our paper is also related to the extensive literature on household saving, borrowing, and consumption, including Caballero (1990), Gourinchas and Parker (2001), Parker and Preston (2005), Christelis, Georgarakos, Jappelli, and Van Rooij (2020) and Agarwal, Chomsisengphet, Yildirim, and Zhang (2021). 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 a housing boom. Our study focuses on the role of mortgage loan in sharping household saving and consumption decisions.

Lastly, our study contributes to the literature on understanding monetary policy in China. While China's monetary policy has a significant impact on both the domestic economy and global financial markets, it remains an area that is not yet thoroughly understood (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 particular focus on the banking system, especially the rise of shadow banking in China. In this paper, we shift the focus to the transmission of monetary policy through the mortgage market in China. Surprisingly, this area has received less attention, despite the pivotal role of the real estate sector in driving China's economic growth. We highlight the channel of prepayment (deleveraging) and find that households engaging in early mortgage prepayment—driven by rigid mortgage rates tend to reduce their consumption. This sheds 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, the restrictions on mortgage refinancing, and procedures to make mortgage prepayments. A brief introduction of wealth management products is also provided. Then, we develop our hypothesis.

2.1. Interest Rates of Mortgage Loans and Limits of Refinancing

On October 8, 2019, the People's Bank of China (PBOC) 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. Before this date, the PBOC used the RMB Benchmark Loan Interest Rates for Financial Institutions (BLIR) as the reference rate for loans and a BLIR-based pricing scheme to determine mortgage rates. The BLIR-based mortgage loans have converted to a LPR-based rate by the end of August 2020. The conversion formula is designed in such a way that the interest rates do not change right after the conversion.¹²

Thus, over our sample period from October 2019 to May 2024, except for a small proportion of fixed-rate mortgages (around 10%), the interest rate of most mortgage loans (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 LPR on *i*'s most recent adjustment date. $Local_Margin_{i,0}$ is the fixed component and determined at the issuance of the mortgage. For instance, the interest rate of a first-home mortgage issued by banks in Beijing on October 10, 2019, was "LPR+55 bps," where the local margin equals 55 basis points (bps). The local margin is set by the prefecture-level policy as a tool for real estate price controls. The heterogeneity in local margins among household *i* can come from (1) the timing of *i*'s home purchase due to the cross-city and time-series variations in policies that determine local margins, and (2) whether it is *i*'s first home or not. Importantly, policy changes in local margins by the local government are only applied to the subsequent new mortgages, not to existing mortgages. This creates rigidity in mortgage rate adjustments.

The second source of mortgage rate rigidity arises from the delayed adjustment of the floating component in Equation (1). Changes to the LPR are applied immediately to new mortgage loans but only take effect for existing loans on their annual adjustment date, which borrowers select as either January 1 or the mortgage issuance date. Once chosen, this adjustment date remains fixed. For example, if the PBOC lowers the LPR by 25 bps on February 20, a new borrower can benefit from the reduction immediately. In contrast,

¹²More details are on the PBOC's website: http://www.pbc.gov.cn/english/130721/3952648/index.html.

existing borrowers would not see the reduced mortgage rate until the next adjustment date (likely January 1 of the following year). Importantly, such delay can be significant and persistent for more than a year in a dynamic setting, as the PBOC gradually cuts interest rates in the easing cycle of monetary policy.

The third and most significant cause of rigidity in mortgage rates in China is the regulatory prohibition on refinancing. Regulations explicitly prevent banks and households from issuing new loans to prepay existing mortgages.¹³ While anecdotal evidence suggests that some households may use short-term loans (e.g., consumer loans) to partially prepay their mortgages, such instances are rare due to significant risks and costs: First, commercial banks explicitly prohibit using new loans to prepay mortgages and reserve the right to terminate loan contracts if violations are detected. Second, these short-term loans often require frequent rollovers, which are both costly and subject to uncertainty regarding future refinancing. According to an internal report from the bank, fewer than 1% of clients are estimated to have utilized other types of loans to finance mortgage prepayments, highlighting the rarity of such behavior. As a result, Chinese households face significant restrictions on resetting their mortgage rates to reflect reduced interest rates, limiting their ability to benefit from monetary easing.

Lastly, it is important to note that mortgage prepayments in China are subject to administrative frictions. Commercial banks typically allow households to make only one prepayment per calendar year. Furthermore, the process—from submitting the application to completing the final payment—can take several months. These constraints could significantly influence households' saving and consumption behaviors. For instance, households often hoard cash in preparation of their once-a-year prepayment opportunity, potentially reducing their immediate consumption.

2.2. Wealth Management Products

Wealth Management Products (WMPs) are investment vehicles offered by financial institutions such as commercial banks and asset management companies. Since the New

 $^{^{13}}$ For one example of such policies and rules, see https://www.gov.cn/zhengce/zhengceku/2021-03/26/content_5596070.htm.

Regulation on Asset Management in 2018, most WMPs have transformed into fixed-income mutual funds using a net asset value (NAV) based pricing scheme. As of December 2024, 97.33% of WMPs are fixed-income funds that primarily invest in low-risk, short-maturity bonds or money market instruments.¹⁴ As a result, changes in benchmark rate are effectively transmitted to WMP returns on a daily basis.

Moreover, such transmission tends to be amplified through the credit channel (Bernanke and Gertler (1995)) and the risk-taking channel (Bauer et al. (2023)).¹⁵ These dynamics suggest that WMP rates adjust more in the direction of benchmark rate movements, a pattern we empirically confirm in Table A1 of the Appendix. The amplification of WMP rate responses to monetary policy further enhances the asymmetric transmission of interest rate changes on household balance sheets.

WMPs play a significant role in the financial portfolios of Chinese households. As of December 2024, over 125 million individuals in China had invested in WMPs, with a total market value of 4.13 trillion USD, according to the annual report by a subsidiary of the China Central Depository and Clearing Company (CCDC).¹⁶ A report by the PBOC shows that WMPs account for 26.6% of households' financial assets, compared to 6.4% in equities.¹⁷ Chinese households tend to view WMPs as low-risk savings instruments offering significantly higher returns than traditional bank deposits (Acharya, Qian, Su, and Yang (2024)). This perception is largely attributed to the historically negligible default rates of WMPs and their superior returns compared to deposits with similar maturities before the New Regulation on Asset Management in 2018 (Feng, Lütkebohmert, and Xiao (2022)).

2.3. Hypothesis

In Appendix B, 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

¹⁴See https://www.chinawealth.com.cn/lc_xwzx/xwgg/202501/P020250117519278053285.pdf.

¹⁵A body of literature documents the "reaching for yield" behavior of fund managers and households in a low-rate environment, e.g., Becker and Ivashina (2015), Choi and Kronlund (2018), and Jiang and Sun (2020). Additionally, Kacperczyk and Schnabl (2013) find that money market funds, which share similarities with WMPs, tend to take on greater risks in an easing environment.

¹⁶See https://www.chinawealth.com.cn/lc_xwzx/xwgg/202501/P020250117519278053285.pdf.

¹⁷See https://finance.sina.cn/money/lczx/2020-04-24/detail-iirczymi8099086.d.html.

a form of savings for households, where the "return" on prepayment is the mortgage rate. When the household's savings/investment return exceeds the mortgage rate, they will choose to save/invest rather than prepay the mortgage. Conversely, when the savings/investment return 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 were originated, we expect to observe mortgage prepayment when the gap between a household's current mortgage rate and their savings returns 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 return. 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 return 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 savings return 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 U.S. market, where mortgage refinancing is more accessible. In the U.S., 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, U.S. 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 mortgage refinancing. Consequently, even though both U.S. and Chinese households' prepayment behaviors demonstrate a nonlinear relationship with the gap between the mortgage rate and savings return, the predictions diverge in other key aspects.

Specifically, the hypothesis for the Chinese market suggests that the tendency for prepayment rises as the rate gap widens in China, while in the U.S., the effect is primarily observed just above zero, resembling a step-like function (Hypothesis 1). Additionally, households with stronger financial positions are inclined to prepay their mortgages more aggressively (Hypothesis 2). Furthermore, it is predicted that Chinese households will reduce their savings and consumption in order to accelerate the prepayment of their mortgages when interest rates decline, instead of increasing their leverage and consumption (Hypothesis 3).

These distinctions are attributed to the rigidity of mortgage rates in China. Confronted with a widening gap between mortgage rates and saving returns, Chinese households are increasingly compelled to use their savings to pay down their mortgages rather than increase their spending, leading to counter-productive monetary policy outcomes.

3. Data

3.1. Loan-level

Our mortgage data is sourced from a major state-owned commercial bank in China, covering the period from October 2019 to May 2024. The starting point of October 2019 is chosen as it marks the implementation of the LPR-based mortgage pricing, preceding China's recent monetary easing cycle. We construct a loan-level dataset by randomly sampling 100,000 loans from a population of millions of outstanding mortgages as of October 2019. This dataset tracks the mortgage payment and consumption behavior of these borrowers throughout the sample period.

The dataset includes detailed mortgage issuance information (e.g., borrower ID, origination location, issuance date, and maturity), monthly loan-level variables (e.g., interest rate, remaining balance, regular and actual monthly payments, and a prepayment indicator), and the collateralized property characteristics (e.g., purchase price and size). Additionally, borrower demographic details (e.g., age, gender, education, and marital status) and monthly financial variables (e.g., total deposits, assets under management (AUM), credit score, and consumption) are also provided. AUM includes the value of deposits, wealth management products, and insurance products on the borrower's bank account. Consumption is measured with the total spending through bank-issued debit cards.¹⁸

The key variable of interest is $Prepay_{i,t}$, a dummy indicating whether mortgage i is fully or partially prepaid in month t. We also define $RateGap_{i,t}$ as the difference between a borrower's mortgage interest rate $(M_{i,t})$ and the prevailing LPR_t .

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 borrowers usually can only prepay once per year). In our regressions, the main dependent variable is a dummy, $Prepay_{t+1\rightarrow t+6}$, which equals one if the borrower prepays between months t + 1 and t + 6, reflecting the time needed for prepayment application, approval, and completion. The mean of $Prepay_{t+1\rightarrow t+6}$ is

¹⁸The consumption data has fewer observations because some borrowers in our sample may not use the bank's cards for spending. We require borrowers to have at least one transaction record per quarter through the bank's cards.

6.3%. The average *RateGap* is positive 0.279% with the 25th and 75th percentiles of -0.004%and 0.695%, respectively. This indicates that most mortgage borrowers are paying interest rates higher than the prevailing LPR during this period, reflecting the downward rigidity of mortgage rates in adjusting to the latest benchmark rate. We use Max(RateGap, 0), which equals the greater value of $RateGap_{i,t}$ and zero, in our regressions; the mean and standard deviation of Max(RateGap, 0) equal 0.412% and 0.438%, respectively.

Panel B compares the characteristics of borrowers who made at least one mortgage prepayment during the sample period with those who did not. Among the 37.5% of borrowers who prepaid, the average prepayment amount is 170,430 yuan (approximately 23,683 USD), which represents 40% of the outstanding mortgage balance of 426,357 yuan (approximately 59,236 USD) at the time of prepayment. This suggests that many prepayments are partial, consistent with the observation that Chinese households typically prepay using savings rather than refinancing. The prepayment amount of 170,460 yuan is also substantial compared to the regular monthly repayment of 3,489 yuan (approximately 485 USD).

Mortgage prepayment is a voluntary choice rather than a randomized treatment. Although our identification strategy does not rely on a direct comparison between prepaying and non-prepaying groups, it is still meaningful to examine their characteristics. Both groups exhibit similar age, loan-to-value (LTV) ratios, credit scores and home sizes. However, RateGap and Max(RateGap, 0) at the time of prepayment are higher for prepaying households (0.333% and 0.459%, respectively) compared to non-prepaying households (0.256% and 0.392%, respectively). Prepaying households tend to have higher levels of education, net wealth, consumption, and monthly repayments than their non-prepaying counterparts.

3.2. City-level

At the city level, we compile data from the bank's entire portfolio of outstanding mortgages for 267 cities over the sample period. For each city c and month t, we calculate: (1) the ratio of prepayments to total mortgage payments ($PrepayCount_{c,t}$) and (2) the fraction of mortgages with RateGap above zero (Frac > 0), following Berger et al. (2021).

We merge this data with UnionPay's monthly city-level consumption dataset. UnionPay, the largest interbank card transaction settlement network in China, processes interbank settlements and clearing transactions for over one billion cardholders globally. Its data has been widely used to study household consumption behavior (e.g., Agarwal, Qian, Seru, and Zhang (2020); Chen, Qian, and Wen (2021, 2023a)). UnionPay's dataset records city-daylevel aggregations of credit and debit card transactions, including spending through pointof-sale (POS) systems and digital wallets (e.g., Alipay and WeChat Pay) linked to bank cards. These records capture total, discretionary, and essential consumption but exclude individual cardholder information. This data cover 221 cities, fewer than our mortgage data, from October 2019 to June 2023. In our empirical tests, we define $\Delta Consumption_{t+1\to t+6}$ as the average monthly growth rate of consumption made through UnionPay cards from month t + 1 to t + 6.

Finally, we incorporate city- and country-level macroeconomic variables from iFind and CSMAR, including GDP per capita, GDP growth, the Purchasing Managers' Index (PMI), housing prices, and the Consumer Price Index (CPI).

Panel C of Table 1 reports summary statistics of the city-level variables. The mean of $PrepayCount_t$ equals 1.0% with a standard deviation of 0.6%. We also calculate $PrepayCount_{c,t+1\to t+6}$, which is the number of mortgage prepayments over month t + 1 to t + 6 scaled by the total number of existing mortgages in city c. The mean of $PrepayCount_{c,t+1\to t+6}$ equals 5.4% with a standard deviation of 3.1%. For the instrument variable, we use Frac > 0, which has a mean of 81.0%, with the 25th and 75th percentiles of 75.8% and 91.8%, respectively. This indicates that in most cities, residents are in a regime where there is a strong incentive to prepay their mortgages. The average growth in consumption is equal to -1.2% per month with a standard deviation of 6.5% during this recession period.

[Insert Table 1 near here]

4. Mortgage Prepayment: Loan-level Analysis

In this section, we analyze Chinese individuals' mortgage prepayment behavior with loan-level data.

4.1. Aggregate Trend

We begin by documenting the aggregate trend of mortgage prepayments using a randomly selected sample of 100,000 mortgage loans from the bank. In Figure 1, we plot the 5-year Loan Prime Rate (LPR) over the sample period (in blue). The PBOC reduced the LPR from 4.85% in September 2019 to 4.65% in April 2020 during the first round of rate cuts. As economic conditions worsened, a second round of reductions began in late 2021, with the LPR falling to 3.95% by May 2024. Alongside the LPR, we calculate the average ratio of mortgage prepayments to total repayments over the subsequent six months (in red). The figure shows that as the PBOC implemented easing measures, prepayments rose to 4.3% by the end of 2021 and exhibited several waves thereafter. In the middle of 2022, prepayments were temporarily halted due to nationwide lockdowns for the Omicron variant of COVID-19 (highlighted by the right gray area in the figure). However, prepayments surged to a peak of 11.5% by early 2023 following the reopening.¹⁹ The observed negative correlation between the LPR and mortgage prepayments (household deleveraging) aligns with our hypothesis that LPR reductions incentivized Chinese households to prepay and deleverage.

[Insert Figure 1 near here]

In Figure 2, we present the time-series trends of several key interest rates. The blue line represents the average interest rate of the bank's existing mortgage loans (issued before September 2019), while the red line shows the LPR. As the LPR decreases, mortgage rates exhibit rigidity, adjusting slowly to the LPR. The gap between the average mortgage rate and the LPR widened from 0.12% in October 2019 to a peak of 0.57% by late 2022. One also observes that the average mortgage rate drops substantially in January of 2020 and 2021, primarily because the LPR adjustment date for many loans is set on January 1st. The PBOC's policy intervention on August 31, 2023, indicated by the vertical dashed line, significantly narrowed the gap to nearly zero before it rose again following the LPR cut by another 25 basis points in February 2024.

[Insert Figure 2 near here]

¹⁹The lockdown in early 2020 (indicated by the left gray area in the figure) was not nationwide and was limited to a few cities, resulting in minimal, if any, impact on prepayment.

The orange line represents the average returns on WMPs maturing each month, which experienced sharper declines than the LPR. Consequently, the gap between the average mortgage rate and WMP returns widened significantly during the monetary easing cycle: it was approximately 0.75% in 2019–2020, despite some volatility in WMP returns, but surged to a peak of 1.90% in the first quarter of 2023 before narrowing to 0.84% to 1.0% in 2024. This pattern underscores the asymmetric rate pass-through on the household balance sheet: interest rate reductions are not effectively transmitted to household liabilities (mortgage loans) but are immediately reflected and amplified in household asset returns (WMPs).

4.2. Interest Rate Gap and Mortgage Prepayment

In the following, we test Hypothesis 1 that Chinese households tend to prepay their mortgages when the gap between their mortgage rates and savings returns becomes positive and increases. As we discussed in Section 2.3, as the central bank cuts interest rates, the asymmetric rate pass-through on the two sides of the household balance sheet can shift their optimal financial choices, prompting mortgage prepayment and deleveraging behavior.

A key empirical challenge is addressing the potential endogeneity of interest rate changes, which may reflect broader macroeconomic conditions influencing household decisions. For example, economic downturns or households' pessimistic expectations could lead to deleveraging through mortgage prepayments, with interest rate cuts being a consequence of such conditions rather than the primary driver of household reactions.

To mitigate these concerns, we first include time (year-month) and city fixed effects to isolate any direct effect from macroeconomic conditions and in some specifications allow these effects to vary across cities by using city-time fixed effects. We also control all known factors, including both macroeconomic variables and borrower and loan characteristics, that may affect household borrowing decisions.

More importantly, our identification strategy exploits within-city-time heterogeneity in borrowers' current rate gap and the nonlinear, threshold-dependent relationship between rate gaps and prepayment propensity. That is, prepayment behavior intensifies only when the rate gap exceeds a critical threshold. For example, a 50-basis-point LPR reduction does not motivate prepayment for households with rates substantially below the LPR, whereas borrowers above the benchmark exhibit pronounced responsiveness. Thus, LPR changes induce heterogeneous prepayment incentives conditional on the distance of a borrower's rate gap from the threshold.

As discussed in Section 2.1, the heterogeneity in rate gaps arises from three main factors: (1) whether the mortgage rate is fixed or floating, (2) the fixed component of the floating rate, $Local_Margin_{i,0}$, in Equation (1), and (3) LPR adjustment schedules. These factors, determined at the time of mortgage origination by local mortgage policies and borrowers' home portfolios, are plausibly exogenous to contemporaneous macroeconomic conditions.

Specifically, we estimate the following individual-month-level panel regression,

$$Prepay_{i,t+1\to t+6} = \alpha + \beta \cdot Max(RateGap, 0)_{i,t} + Controls + \mu_c + \gamma_t + \varepsilon_{i,t}$$
(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. $RateGap_{i,t}$ equals the interest rate of mortgage $(M_{i,t})$ minus the LPR in month *t*. We first present our baseline results using the LPR rate as the proxy for savings return and zero as the threshold; later, we discuss the analysis using other thresholds and alternative proxies. $Max(RateGap, 0)_{i,t}$ equals the greater value of $RateGap_{i,t}$ and zero, which aims to capture the nonlinear effect.²⁰ γ_t and μ_c refer to time and city fixed effects, respectively.

For *Controls*, we follow Berger et al. (2021) and include 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 add 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, to rule out the effect of housing price fluctuations. Standard errors are clustered by time.

[Insert Table 2 near here]

²⁰As shown in Table A3 of the Internet Appendix, our findings remain robust when we use $RateGap_{i,t}$ instead of $Max(RateGap_{i,t}, 0)$, although the R^2 is slightly smaller.

Table 2 presents the results. In columns (1) and (2), we include city fixed effects and time fixed effects. In column (3), we add city-time fixed effects, which rule out any city-time-level economic conditions or factors that could impact prepayment behavior. The coefficients before Max(RateGap, 0) are all positive and statistically significant (*t*-statistics above 8). In terms of economic magnitude, the coefficient 0.017 in column (3) indicates that a onestandard-deviation increase in Max(RateGap, 0) corresponds to a 12.0% increase in the prepayment indicator relative to its sample mean (12.0% = 0.438 × 0.0172 / 0.063). In columns (4) and (5), we define *PrepayPartial* and *PrepayFull*, which equal one if a partial prepayment or a full prepayment is made, respectively, and run the same regression. We find that the main result remains significant and robust to both partial and full mortgage prepayments.

In Table A2 of the Internet Appendix, we replace the dependent variable, $Prepay_{i,t+1\rightarrow t+6}$, measured over a 6-month window, with monthly dummies, $Prepay_{i,t+1}$, ..., $Prepay_{i,t+6}$, to examine the dynamics of the effects. The results indicate that prepayment behavior is evenly distributed across the six-month period, with all *t*-statistics consistently around 10. Also, our results are robust to controlling individual fixed effects, as shown in Panel B of Table A2. This approach eliminates the potential impact of the fixed component, $Local_Margin_{i,0}$, such that the identification primarily relies on loan-level changes in mortgage rates above the threshold.

In Panel B of Table 2, we test various threshold values to identify the best fit for the data. Specifically, we calculate Max(RateGap, X), where $X \in \{-0.6\%, -0.3\%, 0\%, 0.3\%, 0.6\%\}$, and re-estimate the regression from column (3) of Panel A. While the results are consistent across all specifications, the threshold value X = 0 yields the highest R^2 , supporting our choice of zero as the primary threshold in our analysis. This finding also suggests that Chinese households closely compare their mortgage rates to the LPR when making prepayment decisions, likely because it is the benchmark rate most frequently referenced by market observers and the media.

We visualize this relationship between rate gap and mortgage prepayment in Figure 3, following the methodology of Berger et al. (2021). We estimate a regression of the prepayment dummy $(Prepay_{i,t+1\to t+6})$ 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. We observe that the positive correlation between prepayment and *RateGap* emerges only in the positive region of *RateGap*, while the correlation is insignificant in the negative region. This pattern reveals a "kink" around zero, which motivates the use of $Frac > 0_{c,t}$ as an instrumental variable in our city-level analysis.

[Insert Figure 3 near here]

Alternative proxies of savings returns Based on our hypothesis, households compare their mortgage rates and the returns that they earn from savings. Savings returns at the household level are not directly observable, and in our baseline setting, we use the LPR as a proxy as it is the most prominent reference rate for households and market observers in China. Nonetheless, we also consider a set of alternative proxies that can potentially track households' actual returns on savings. As discussed in Section 2, given that WMPs have become the main way for Chinese households to save their financial wealth, it is a natural choice to use WMP returns as the proxy.

Specifically, we adopt three commonly used reference rates of WMP returns for our analysis. The reference rate is designed to reflect the average return of WMPs of a kind, and the data is provided by one of the largest WMP database vendors, Southern Finance Omnimedia Group.²¹ These reference rates are: (1) the average realized return of WMPs maturing in the current quarter, (2) the average benchmark return of newly issued WMPs, and (3) the average annualized return of cash-like WMPs. We recalculate *RateGap* using each of the WMP reference rates and various threshold values.

[Insert Table 3 near here]

We report the results in Table 3. Panel A shows the summary statistics of the rate gaps using zero as the threshold. On average, the rate gap based on LPR is the smallest (0.28%), while the one based on cash-like WMPs is the largest (2.11%). This is driven by

²¹Southern Finance Omnimedia Group's dataset covers over 250,000 WMPs issued by more than 400 commercial banks. Website: https://gym.sfccn.com/portal.

WMP characteristics such as liquidity and risk. Due to these differences, the "kink" points of the three alternative gaps should not be zero. Thus, we explore different sets of critical values (X) to identify the "kink" with the highest explanatory power based on \mathbb{R}^2 for each alternative proxy.

Panels B to D present the results. First, one can see that across various choices of savings returns proxies and threshold values, the coefficients before Max(RateGap, X) are positive and statistically significant at the 1% level, consistent with our hypothesis. Second, the highest R^2 among specifications using WMP returns as the proxy is lower than the primary setting, which uses the LPR and a zero threshold and is shown in columns (3) of Table 2, Panel A.

Our analysis concludes that using the LPR and a zero threshold can most effectively capture household prepayment behavior, though the advantage is marginal. While WMP returns could theoretically serve as a better proxy for savings returns, the aggregate measures we have could introduce significant noise due to heterogeneity in household access to WMP products and varying preferences for risk and liquidity. Without granular data on the specific WMPs in which households invest, using average WMP returns could poorly fit the data compared to using the LPR. Based on this finding, we adopt the LPR as the primary proxy for the remainder of our analysis.

Cross-sectional heterogeneity The nonlinear relationship between *RateGap* and mortgage prepayment in China resembles findings from the U.S. For instance, Berger et al. (2021) document that U.S. households tend to prepay mortgages when the rate gap between their existing and new loans turns positive.

Despite this similarity in empirical patterns, the underlying economic mechanisms are distinct between China and the U.S. In the U.S., where refinancing is widely available, Berger et al. (2021) show that it is the low-income or financially constrained households who are more responsive to a positive rate gap, driven by the incentive to reduce interest expenses. In contrast, in China, where refinancing options are limited, it should be the case that households with higher financial resources—such as greater savings or income—are more likely to prepay, as outlined in Hypothesis 2 in Section 2.3.

We conduct a cross-sectional analysis using three dummy variables (HighChar) to identify borrowers in the top 30% of the sample by AUM, credit score, and education level above a bachelor's degree. We add interaction terms between each dummy variable and Max(RateGap, 0) into the baseline regression in Equation (2), and the results, reported in Table 4, confirm our conjecture. The coefficients before the interaction terms are all positive and significant at the 1% level, with meaningful economic magnitudes. For example, in column (1), the coefficient on $Max(RateGap, 0) \times HighAUM$ is 0.0165 (t-statistic = 9.75), indicating that high-AUM households are 38.66% more responsive to rate gaps compared to others, given the baseline coefficient on Max(RateGap, 0) is 0.0119 (t-statistic = 16.06). The coefficients on the dummy variables themselves are also positive, suggesting that affluent households are in general more likely to prepay on average.

Figure 4 illustrates these effects by replicating the analysis in Figure 3 for subsamples based on AUM (Panel A), credit scores (Panel B), and education levels (Panel C). The visual patterns align with the regression results. Overall, the cross-sectional analysis highlights distinct prepayment behaviors in the absence of refinancing options, offering a sharp contrast to evidence from the U.S.

[Insert Table 4 and Figure 4 near here]

4.3. Saving and Consumption Behavior After Prepayment

Next, we investigate how prepaying households adjust their saving and consumption behaviors. As outlined in Hypothesis 3 in Section 2.3, our framework predicts that prepaying borrowers significantly reduce both total savings and consumption following the prepayment. This contrasts with the implications of mortgage refinancing, where reduced interest expenses are expected to increase consumption, as shown in Berger et al. (2021).

For each month, we compute the total deposits and liquid assets (AUM) in each borrower's bank account. AUM include bank 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.²² We acknowledge that one

²²A majority of Chinese households do not use credit cards.

limitation of this analysis is the lack of data on borrowers' saving and consumption activities across other banks if they hold multiple accounts. However, as long as their preferred bank account remains the same before and after prepayment, we can reliably identify relative changes in their saving and consumption behaviors.

Specifically, 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 a prepayment by 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 -0.779, 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), the dependent variable is consumption, and here we require the borrower to have at least one consumption record in each quarter to be included in the sample. We find that the coefficient before AfterPrepay is -0.0206 (t-statistic= -2.65). This indicates that households also reduce their consumption moderately by about 2% following prepayment. These results are consistent with Hypothesis 3 that households allocate a significant portion of their liquid assets to mortgage prepayments without refinancing, which leads to further reductions in consumption.

4.4. A Quasi-natural Experiment: Policy Intervention on Mortgage Rate Rigidity

To strengthen our identification strategy and establish the causal effect of the rate gap on mortgage prepayment and consumption, we leverage a policy initiative introduced by Chinese regulators in 2023. On August 31, 2023, the PBOC together with local governments announced that certain borrowers would be eligible to reset the local margin of their existing mortgage loans to the lower first-home margin, even if they were not classified as first-home borrowers at the time of purchase. The key element of the policy is to redefine the "first home" criteria: Prior to September 2023, a first home was defined as the borrower's first property purchase; Post-September 2023, a first home is redefined as the only property currently owned by the borrower and their family, allowing eligible mortgages to reset to the lower first-home margin applicable at the time of mortgage issuance.

For example, if a borrower previously purchased Property A and then Property B at time t, the local margin for A, as the first home, is typically lower than that for B (non-first home). Suppose that the borrower later sold Property A, the local margin on the mortgage for Property B can now be reduced to the time t's first-home rate under the new policy. However, if both properties are still owned, the margins remain unchanged. The policy aims to alleviate households' interest rate burdens, stimulate consumption and investment, and reduce mortgage prepayments, as emphasized in the PBOC's announcement.²³ By making interest rate pass-through directly onto mortgage rates, this policy can be viewed as an effective intervention that alleviates mortgage rate rigidity for some households.

We exploit this policy as a plausibly exogenous shock to mortgage rates and, consequently, to the rate gap. The treatment group consists of households benefiting from the policy, while the control group includes those unaffected. For this analysis, the bank provides us the data of all outstanding mortgage loans in the four tier-one cities (Beijing, Shanghai, Shenzhen, and Guangzhou) from October 2022 to May 2024. We identify that about 25% of loans in the sample benefit from the policy, with an average interest rate reduction of 50 basis points.

We conduct a difference-in-differences (DID) analysis to examine the impact of the rate gap on prepayments and consumption. If the relationship between the rate gap and prepayment is causal, a reduction in mortgage rates (narrowing the rate gap) should decrease the likelihood of mortgage prepayments. This result would align with the policy's objectives, supporting the regulator's aim to reduce prepayments and promote consumption.

We estimate the following DID regression:

$$Prepay_{i,t} = \alpha + \beta \cdot Treat_i \times Post_t + Controls + \mu_i + \gamma_{c,t} + \varepsilon_{i,t}$$
(3)

 $^{^{23}}$ For policy details, see http://www.pbc.gov.cn/rmyh/3963412/3963426/5050299/index.html and http://finance.people.com.cn/n1/2023/0901/c1004-40068916.html.

where $Prepay_{i,t}$ is a dummy variable equal to one if individual *i* makes 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.²⁴ $Post_t$ is a dummy variable equal to one if month t is in or after September 2023, and zero otherwise. We have the same set of control variables as in the previous tables and include city-time and individual fixed effects.

[Insert Table 6 near here]

Table 6 reports 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 (t-statistic = -5.76). This indicates that households affected by the policy experience a 25.51% greater reduction in the likelihood of prepayment compared to unaffected households, relative to the sample mean (25.51% = 0.005/0.0196). These findings align with our hypothesis.²⁵

To verify the parallel trends assumption, we plot the dynamic effects of the policy on prepayments in Panel A of Figure 5. The analysis includes a series of interaction terms, $Treat_i \times Post_k$, where k represents the number of quarters relative to the event month, with k = -1 serving as the benchmark. Panel A displays the coefficients of these interaction terms along with their confidence intervals. The coefficients for post-event periods are negative and statistically significant, while those for pre-event periods are indistinguishable from zero, supporting the validity of the parallel trends assumption.

[Insert Figure 5 near here]

We next investigate the impact of the policy on household consumption. If mortgage prepayments constrain consumption, we expect a policy that narrows rate gaps and discourages prepayments to lead to higher consumption. Using the same DID framework as in Equation (3), we replace the dependent variable with the natural logarithm of consumption, $LogConsumption_{i,t}$. The results, presented in Panel B of Table 6, indicate that households increase consumption following the mortgage rate reduction. For example, in column (2), the

²⁴Our results are robust to replacing $Treat_i$ with the reduction in rate gaps; see Appendix Table A4.

²⁵In Appendix Table A5, we run the regressions separately for partial and full prepayments and find a significant reduction in both types of prepayments following the policy.

interaction term coefficient is 0.0068 (*t*-statistic = 2.72), suggesting that affected households experience a 0.68% larger increase in consumption compared to unaffected households.

We also confirm the parallel trends assumption in Panel B of Figure 5. The results show significantly larger increases in consumption for affected households during post-event periods, with no discernible differences during pre-event periods.

Overall, the results in this subsection provide causal evidence of how rate gaps can induce mortgage prepayments and reduce household consumption. The PBOC's policy intervention, which directly reduces local mortgage rate margins, effectively mitigates the downward rigidity of mortgage rates and enhances monetary policy transmission.

5. Implications to Monetary Policy Transmission

In the previous section, we present loan-level evidence demonstrating that mortgage rate rigidity—arising from frictions in rate pass-through within the mortgage market—can lead to unintended consequences, including voluntary household deleveraging and reduced consumption. In this section, we extend the analysis to the city level to investigate how mortgage rate rigidity influences the macroeconomic outcomes of monetary policy.

5.1. Frac > 0 and City-level Mortgage Prepayment

We begin by constructing a variable to aggregate Max(RateGap, 0) and link it to total mortgage prepayments at the city level. We adopt the methodology of Berger et al. (2021) to calculate the proportion of outstanding mortgages with interest rates exceeding the LPR for each city-month, denoted as $Frac > 0_{c,t}$. This approach is motivated by the results in Table 2 and Figure 3, which indicate that the effect of $RateGap_{i,t}$ on prepayment is significant only when $RateGap_{i,t}$ is positive. By using Frac > 0, we exploit the "kink" in the relationship between $RateGap_{i,t}$ and prepayment decisions, thereby strengthening the identification in our tests and mitigating concerns that the level of RateGap may be correlated with city-time level factors influencing prepayment behavior.

In our city-level dataset, constructed from the full sample of mortgage loans issued by the bank, the average of Frac > 0 is 81.0%, with a standard deviation of 16.2%. This indicates that, despite cross-city variations, the majority of cities face prepayment pressure, as a substantial share of their residents hold mortgage rates above the current benchmark rate. As discussed in Section 2, the cross-sectional heterogeneity in Frac > 0 reflects the path of each city's historical policies on home purchases and local mortgage rate margins, weighted by the timing of residents' home purchase waves. Our empirical premise is that, given this path-dependent nature, Frac > 0 is plausibly uncorrelated with current city-level economic conditions affecting prepayment behavior, after controlling for time and city fixed effects as well as other relevant macroeconomic variables.

The dependent variable, labeled as $PrepayCount_{c,t+1\to t+6}$, is the number of mortgage prepayments over month t + 1 to t + 6 scaled by the total number of existing mortgages in city c. Specifically, we estimate the following regression,

$$PrepayCount_{c,t+1\to t+6} = \alpha + \beta \cdot Frac > \theta_{c,t} + Controls + \mu_c + \gamma_t + \varepsilon_{c,t}.$$
(4)

Controls represent a set of macroeconomic variables such as PMI, the changes in CPI, GDP growth, GDP per capita, average housing price, and monthly changes in housing price. We also include city and time fixed effects. The time fixed effects can rule out the possible time-series 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.

[Insert Table 7 near here]

As shown in column (1) of Table 7, 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 $(14.0\% = 0.0468 \times 0.162/0.054)$.²⁶

²⁶We conduct several robustness tests in the Internet Appendix. First, we replace the dependent variable, $PrepayCount_{c,t+1\to t+6}$, measured over a 6-month window, with monthly dummies, $Prepay_{c,t+1}, \dots, Prepay_{c,t+6}$, to examine the dynamics of the effects. We find similar effects for most of these monthly dummies in Panel A of Table A6. Second, we use an alternative prepayment ratio based on the value of prepayments to the total value of mortgage repayments and find consistent results; see Panel B of Table A6. Third, we replace Frac > 0 with $RateGap_City_{c,t}$, which is the difference between the average interest rate of existing mortgages in city c and the LPR_t . As shown in Table A7, our results remain unchanged.

Similar to our analysis in Panel B of Table 2, we experiment with different values of the "kink." That is, We compute Frac > X, where X takes values of -0.6%, -0.3%, +0.3%, and 0.6%. The purpose of this analysis is to identify, at the city level, the precise "kink" that households use as a reference point. The results, presented in the remaining columns of Table 7, show significant and positive coefficients across all specifications. Notably, the regression using Frac > 0 produces the highest R^2 compared to other specifications. This finding aligns with the loan-level results reported in Panel B of Table 2. Accordingly, we use Frac > 0 as the instrumental variable in subsequent analyses to examine the causal impacts of mortgage prepayments on consumption.

5.2. Aggregate Consumption

In Table 5, we find that prepaying households tend to reduce their spending following mortgage prepayment. Given the limitations in refinancing, households are compelled to finance their prepayments through savings, which leads to a contraction in consumption. A natural question arises as to whether this effect extends to the aggregate level—a more economically significant question for policymakers seeking to evaluate the effectiveness of monetary policy. According to a survey by the PBOC, 96% of urban households own real estate properties, and 43.4% carry mortgage debt.²⁷ This indicates that the mechanism proposed in this paper likely generates substantial effects at the macro level.

To explore this, we use proprietary data from UnionPay to measure aggregate household consumption at the city level. Unlike the one we use for loan-level analyses, this consumption measure covers not only mortgage borrowers but also other residents. As described in Section 3, consumption is measured based on credit and debit card transactions, which include spending through POS systems and digital wallets such as Alipay and WeChat Pay linked to UnionPay bank cards. These records provide total spending, as well as its breakdown into discretionary and essential spending.

The empirical challenge is to identify the causal effect of LPR adjustments on household consumption through the rate gap and mortgage prepayment channel. Interest rate changes may reflect broader economic conditions, potentially driving the observed correlation between

²⁷See the report, https://finance.sina.cn/money/lczx/2020-04-24/detail-iirczymi8099086.d.html.

mortgage prepayments and reduced consumption. For instance, pessimism about the local economy could lead residents of a city to reduce consumption and deleverage by prepaying mortgages with savings.

To address this issue, we employ 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 over the period from months t + 1 to t + 6. The validity of this approach hinges on the exclusion restriction, which assumes that $Frac > 0_{c,t-1}$ does not directly influence the city's total consumption during months t + 1 to t + 6. We argue that this assumption is plausible: because Frac > 0 is path-dependent on the city's historical mortgage policies and the timing distribution of mortgage issuance, it is unlikely to be directly related to current economic conditions or borrowers' expectations.

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

$$\Delta Consumption_{c,t+1\to t+6} = \alpha + \beta \cdot PrepayCount_{c,t} + Controls + \mu_c + \gamma_t + \varepsilon_{c,t}, \qquad (5)$$

where the dependent variable is the average monthly growth rate of total consumption of city c over month t + 1 to month t + 6. Other control variables and fixed effects are the same as the regression of Equation (4).

[Insert Table 8 near here]

Table 8 presents the results. In the first-stage regression shown in column (1), Frac > 0 exhibits a strong positive correlation with the mortgage prepayment ratio. This is consistent with the findings in Table 7. The *F*-stat equals 28.30 and rules out the concern of a weak IV.

In the second-stage regression in column (2), the coefficient before the instrumented PrepayCount is -8.4770 with a t-statistic = -6.49. The economic magnitude is also substantial: a one-standard-deviation increase in the fraction of prepayments is associated with a 5.09% (= 0.006×8.4770) decrease consumption growth. In column (3), we perform an OLS regression of consumption growth on prepayment. The coefficient before PrepayCount is smaller in magnitude, at -3.6741 (t-statistic = -6.92), indicating a 2.20% decrease in

consumption growth. Overall, these findings suggest that lower interest rates, instead of stimulating household consumption, actually curtail it when mortgage rates are rigid. This result contrasts with evidence from the U.S. and runs counter to the intended objectives of expansionary monetary policy.

Moreover, our hypothesis suggests that the reduction in consumption should be more pronounced for discretionary (non-necessity) spending, and the data confirms this prediction. Using the UnionPay data, we adopt two categorizations of household spending to analyze the differential effects. The first categorization distinguishes between essential and discretionary consumption: essential spending includes expenditures on food, gasoline, utilities, household services, and telephone services, while discretionary consumption covers spending on alcohol, tobacco, automobiles, electronic devices, entertainment, and inter-city transportation.

The results are presented in Panel A of Table 9. For both IV and OLS regressions, the coefficients on *PrepayCount* are larger in magnitude and more significant for discretionary consumption compared to essential consumption. For instance, in the IV regression, the coefficient on *PrepayCount* is -0.0324 (*t*-statistic = -0.02) for essential consumption, whereas it is -8.4640 (*t*-statistic = -2.40) for discretionary consumption.

The second categorization is based on the size of transactions, as larger expenditures are more likely associated with durable goods and luxury activities. We define small versus large spending using a threshold of 1,000 yuan (or 136 USD). The results, reported in Panel B, show that large-scale consumption is more significantly affected by mortgage prepayments than small expenditures. For example, in the IV regression, the coefficient on *PrepayCount* is -0.7749 (*t*-statistic = -0.65) for small consumption, while it is -8.5001 (*t*-statistic = -3.40) for large consumption.

[Insert Table 9 near here]

5.3. Policy Implications

Finally, we discuss the implications of our findings for the effectiveness of monetary policy in China. In our city-level analysis, we use Frac > 0 as an instrumental variable to identify the causal effect of LPR adjustments on household consumption through the mortgage prepayment channel. However, Frac > 0 can also be interpreted as the degree to which mortgage rate rigidity can impede the intended outcomes of monetary policy. Specifically, in cities where a larger proportion of borrowers face mortgage rates above the benchmark, rate cuts are unlikely to stimulate household borrowing and consumption effectively. Instead, they may have counterproductive effects. This interpretation contrasts with that of Berger et al. (2021), who view Frac > 0 as a measure of monetary policy "space." The divergence stems from the unique mortgage market frictions in China, which create significant rigidity in mortgage rates. These frictions limit the ability of rate cuts to pass through to households' debts, thereby undermining the expansionary objectives of monetary policy.

We illustrate this conjecture by estimating the following OLS regression,

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

where $HighFrac_{c,t-1}$ is a dummy variable that equals one if $Frac > 0_{c,t-1}$ is among the top 30% of the sample, and zero otherwise. ΔLPR_t refers to the monthly changes in LPR. Controls include $HighFrac_{c,t-1}$ and the same set of the control variables and fixed effects as in Table 8. 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.²⁸ If HighFrac measures "impediment" in monetary policy transmission, we would expect β to be positive. The results presented in Table 10 are consistent with this conjecture; the coefficient before the interaction term is 0.0793 (t-statistic = 2.02). 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 10 near here]

A natural policy implication of our findings is that, to enhance the effectiveness of monetary policy in stimulating consumption, it is critical to reduce Frac > 0—that is, to lower the interest rates on outstanding mortgages. Our event study, discussed in Section 4.4,

 $^{^{28}\}Delta LPR_t$ is subsumed by the time fixed effects.

provides supportive micro-level evidence. Similarly, Agarwal et al. (2022) examine a comparable recession episode in China around 2008 and document an immediate increase in consumption among mortgage borrowers following a universal mortgage rate cut of 2.3%. These unconventional measures can effectively break mortgage rate rigidity, allowing interest rate cuts to be transmitted directly to borrowers and, consequently, to enhance household consumption. The results presented in this section provide supportive macro-level evidence for this conjecture.

6. Conclusion

The mortgage market plays a critical role in monetary policy transmission, as frictions in this market can impede interest rate pass-through to households, influencing their borrowing and consumption behaviors. This paper proposes a new mechanism through which mortgage rate rigidity can lead to counterproductive outcomes for expansionary monetary policies. Specifically, mortgage rate rigidity creates an asymmetry in rate pass-through on household balance sheets: while mortgage rates adjust slowly to changes in benchmark rates, household savings returns, particularly those linked to investments such as WMPs, respond immediately and often amplify these changes. When the central bank lowers interest rates, the widening gap between borrowing costs (mortgage rates) and savings returns motivates households to prepay their mortgages using savings, consequently reducing consumption.

In China, this rigidity stems largely from the market power of state-owned banks and regulatory restrictions on mortgage refinancing. This mechanism, however, is generalizable to other countries, particularly emerging markets, where frictions such as fixed-rate mortgages or high refinancing costs could significantly hinder the transmission of monetary policy to mortgage loans.

We demonstrate that this mechanism explains the unprecedented wave of mortgage prepayments in China between 2019 and 2024. Using loan-level data from a large state-owned bank, we show that households are significantly more likely to prepay when the gap between their mortgage rate and the benchmark rate becomes positive and widens. Importantly, households prepay with their savings, rather than through refinancing, leading to delever-
aging and a reduction in consumption. These effects are not driven by macroeconomic variables, local real estate market conditions, or borrower and property characteristics. Using the policy intervention in September 2023 as a quasi-natural experiment, we provide causal evidence for this mechanism.

At the macro level, combined with UnionPay's spending data, we find that cities with higher proportions of borrowers facing positive rate gaps experience greater mortgage prepayment and more pronounced consumption reductions following rate cuts. This suggests that mortgage prepayments have significantly weakened monetary policy transmission in China.

Our findings align with and support the PBOC's recent policy reforms aimed at addressing mortgage rate rigidity. On September 29, 2024, the PBOC introduced a new mortgage pricing mechanism featuring two key changes. First, local margins, previously fixed for the loan term, can now float based on market conditions, allowing borrowers to negotiate downward adjustments when their margins exceed those of newly issued loans. Second, the adjustment frequency for mortgage rates has been shortened from one year to as little as three months, ensuring faster alignment with benchmark rate changes. These measures can reduce mortgage rate rigidity, enhancing the effectiveness of rate pass-through to household borrowing.

Our study highlights that allowing mortgage rates to fully float with the central bank's benchmark rate is essential for effective monetary policy transmission. While deregulating mortgage refinancing may help in the Chinese context, the most effective solution, in general, is to ensure mortgage rates are directly linked to the benchmark rate, as refinancing can be costly and less accessible for some borrowers.

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

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



Fig. 2. Time trends of the LPR, average mortgage rates, and WMP returns

This figure plots the trends of average mortgage rates, the LPR, and realized WMP returns from October 2019 to May 2024. The mortgage rate is the average existing mortgage rate calculated using the bank's all mortgage loans. The realized WMP return is the average realized returns of Wealth Management Products (WMPs) maturing in the current quarter. The black dashed line marks the PBOC's policy intervention on August 31, 2023.



Fig. 3. 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 prepayments (in decimal) for each gap bin, as well as their 95% confidence intervals. These fractions are estimated using the following regression:

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

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(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), LTV², mortgage age dummies, log AUM, gender dummies, education, internal credit score, and city fixed effects. All variables are defined in Appendix A.



(c) Panel C: By CreditScore

Fig. 4. Interest rate gaps, borrower 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 in 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 3. In Panel A, we present the results for the high-AUM individuals (AUM in the top 30%) and low-AUM individuals separately; In Panel B, we present the results for the high-education individuals (education level \geq Bachelor) and low-education individuals separately; and in Panel C, we present the results for the highcredit score individuals (credit score in the top 30%) and low-credit score individuals separately.



(b) I aller D. Collsain

Fig. 5. 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, $Treat_i \times Post_k$, in the DID regression. The third quarter of 2023, when the policy was announced, serves as the benchmark. We plot the coefficients on the interaction terms and their 95% confidence intervals. All regressions include individual fixed effects and city-time fixed effects. Standard errors are clustered at the time level.

Table 1: Summary statistics

This table presents the summary statistics of the main variables. Panel 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						
	Ν	Mean	STD	P25	P50	P75
$Prepay_t$	4142307	0.011	0.106	0.000	0.000	0.000
$Prepay_{t+1 \rightarrow t+6}$	4142307	0.063	0.243	0.000	0.000	0.000
$PrepayPartial_{t+1 \rightarrow t+6}$	4142307	0.024	0.155	0.000	0.000	0.000
$PrepayFull_{t+1 \to t+6}$	4142307	0.041	0.227	0.000	0.000	0.000
M	4142307	4.750	0.690	4.200	4.750	5.240
RateGap(%)	4142307	0.279	0.628	-0.040	0.250	0.695
Max(RateGap, 0)	4142307	0.412	0.438	0	0.250	0.695
Age	4142307	38.926	8.342	33.000	38.000	44.000
MortgageAge	4142307	5.779	3.345	3.000	5.000	8.000
HighEduc	4142307	0.292	0.455	0.000	0.000	1.000
Male	4142307	0.640	0.480	0.000	1.000	1.000
CreditScore	4142307	775.000	59.000	767.000	784.000	801.000
LTV	4142307	0.434	0.190	0.290	0.465	0.590
AUM	4142307	20186.840	61051.270	536.950	2203.030	9358.090
Deposit	4142307	16714.950	49800.75	186.100	2185.210	8362.400
Consumption	1026503	13872.110	21241.290	902.300	4723.170	15561.460
Log(AUM)	4142307	7.592	2.538	6.288	7.698	9.144
Log(Deposit)	4142307	7.069	2.968	5.232	7.688	9.032
Log(Consumption)	1026503	8.310	2.067	7.173	8.581	9.729
HousingPrc	4142307	11399.000	9429.000	6093.000	8682.000	13269.000
$\Delta HousingPrc$	4142307	0.001	0.113	-0.035	0.000	0.037

	IDs without Prepayment	IDs with Prepayment
Number of Individuals	62461	37539
M(%)	4.699	4.871
RateGap(%)	0.256	0.333
Max(RateGap, 0)	0.392	0.459
Age	39.320	37.939
MortgageAge	6.116	4.909
HighEduc	0.258	0.372
Male	0.657	0.602
CreditScore	772.394	780.942
HouseArea	105.113	107.660
HousingPrc	10049.000	11518.000
$\Delta HousingPrc$	0.001	0.002
LTV	0.440	0.419
AUM	17888.900	25543.490
Deposit	14848.400	21072.980
Consumption(Median)	4606.960	5357.060
Regular Repayment	2694.160	3489.84
Prepayments	NA	170430.090

Panel B: Individuals without prepayments vs individuals with prepayments

Panel C: Variables for city-level analysis

	Ν	Mean	STD	P25	P50	P75
$PrepayCount_{t+1 \rightarrow t+6}$	12950	0.054	0.031	0.036	0.048	0.066
$PrepayCount_t$	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
$\Delta HousingPrc$	12950	0.001	0.085	-0.031	0.000	0.033
Log(HousingPrc)	12950	8.837	0.454	8.549	8.746	9.004
$\Delta Consumption_{t+1 \to t+6}$	6426	-0.012	0.065	-0.044	-0.016	0.012

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 columns (1) to (3) of Panel A, the dependent variable is $Prepay_{i,t+1\rightarrow t+6}$, a binary indicator equal to one if individual i either partially or fully prepays their mortgage between months t+1 and t+6, and zero otherwise. In column (4), $PrepayPartial_{i,t+1\to t+6}$ equals one if individual i partially prepays their mortgage between months t + 1 and t + 6, and zero otherwise. In column (5), $PrepayFull_{i,t+1 \to t+6}$ equals one if individual i fully prepays their mortgage between months t+1 and t+6, and zero otherwise. RateGap_{i,t} is the mortgage rate of individual i minus the LPR in month t. $Max(RateGap, 0)_{i,t}$ 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 bank, mortgage age dummies, and 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. We include city fixed effects and time fixed effects in columns (1) and (2), and city-time fixed effects in columns (3) to (5). In Panel B, $Max(RateGap, X)_{i,t}$ equals the greater value of $RateGap_{i,t}$ and X percentage points. All variables are defined in Appendix A. 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: Positive interest rate gap and prepayment						
	(1)	(2)	(3)	(4)	(5)	
		$Prepay_{t+1 \to t+6}$		PrepayPartial	PrepayFull	
Mar(BateGan 0)	0 0203***	0 0239***	0.0179***	0 0082***	0 0095***	
max(nancoup, 0)	(8.99)	(15.71)	(18.33)	(13.08)	(18.05)	
Log(AUM)	(0.00)	0.0048***	0.0048***	0.0017***	0.0032***	
5()		(16.23)	(16.73)	(16.19)	0.01704^{***}	
LTV		-0.0911***	-0.0909***	-0.1162***	-0.0738***	
		(-22.13)	(-22.12)	(-18.21)	(-15.97)	
LTV^2		0.0116^{***}	0.0121^{***}	0.0149^{***}	0.0103^{***}	
		(4.25)	(4.44)	(6.23)	(3.29)	
CreditScore		0.0000	0.0000	0.0000^{***}	0.0000	
		(0.30)	(0.34)	(8.68)	(0.11)	
HighEduc		0.0148***	0.0154***	0.0089***	0.0083***	
16.1		(12.59)	(13.00)	(14.22)	(16.11)	
Male		-0.0100***	-0.0103***	-0.0039***	-0.0055***	
		(-31.40)	(-29.21)	(-19.22)	(-22.68)	
GDP Growth		0.0009				
CDD Dom Com		(0.14)				
GDP Per Cap		-0.0192^{+++}				
Log(HousingPrc)		(-0.33)				
Log(110ustrig1 rc)		(1.65)				
$\Delta HousingPrc$		0.0000				
<u> </u>		(1.19)				
City FE	YES	YES	-	_	_	
Time FE	YES	YES	-	-	-	
City-Time FE	NO	NO	YES	YES	YES	
Within R^2	0.12%	0.92%	0.60%	0.31%	0.55%	
Obs.	4142307	4142307	4142307	4142307	4142307	

	(1)	(2)	(3)	(4)	(5)
X =	-0.6%	-0.3%	$\frac{Prepay_{t+1\to t+6}}{0\%}$	0.3%	0.6%
Max(RateGap, X)	$00145^{***} \\ (18.22)$	0.0165^{***} (18.37)	$\begin{array}{c} 0.0172^{***} \\ (18.33) \end{array}$	$\begin{array}{c} 0.0163^{***} \\ (18.54) \end{array}$	$\begin{array}{c} 0.0133^{***} \\ (16.31) \end{array}$
Controls City-Time FE Within R^2 Obs.	YES YES 0.5954% 4142307	YES YES 0.5962% 4142307	YES YES 0.5969% 4142307	YES YES 0.5965% 4142307	YES YES 0.5844% 4142307

Panel B: Alternative threshold values

Table 3: Alternative interest rate gaps and prepayments

This table presents the results of the baseline regressions using alternative interest rate gaps. $RateGap_MaturingWMP_{i,t}$ is the mortgage rate of individual *i* minus the average realized return of WMPs maturing in month *t*. $Max(RateGap_MaturingWMP, X)_{i,t}$ equals the greater value of $RateGap_MaturingWMP_{i,t}$ and X percentage points. $RateGap_NewlyIssuedWMP_{i,t}$ is the mortgage rate of individual *i* minus the average benchmark return of newly issued WMPs in month *t*. $Max(RateGap_NewlyIssuedWMP, X)_{i,t}$ equals the greater value of $RateGap_NewlyIssuedWMP_{i,t}$ and X percentage points. $RateGap_CashLikeWMP_{i,t}$ is the mortgage rate of individual *i* minus the average return of cash-like WMPs in month *t*. $Max(RateGap_CashLikeWMP, X)_{i,t}$ equals the greater value of $RateGap_CashLikeWMP_{i,t}$ and X percentage points. Panel A presents the summary statistics of the interest rate gaps. In Panels B to D, the dependent variable is $Prepay_{i,t+1\rightarrow t+6}$. 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 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: Summary statistics of interest rate gaps						
	Mean	P25	P50	P75		
RateGap(%)	0.279	-0.040	0.250	0.700		
$RateGap_MaturingWMP$	0.977	0.490	1.010	1.485		
$RateGap_NewlyIssuedWMP$	0.893	0.538	0.900	1.318		
$RateGap_CashLikeWMP$	2.105	1.790	2.090	2.570		

	(1)	(2)	(3)	(4)	(5)
			$Prepay_{t+1 \to t+}$	6	
X =	0.4%	0.7%	1%	1.3%	1.6%
$Max(RateGap_MaturingWMP, X)$	$\begin{array}{c} 0.0124^{***} \\ (16.89) \end{array}$	$\begin{array}{c} 0.0112^{***} \\ (17.42) \end{array}$	0.0097^{***} (18.84)	0.0084^{***} (16.71)	0.0078^{***} (13.58)
Controls City-Time FE Within R^2 Obs.	YES YES 0.5895% 4142307	YES YES 0.5913% 4142307	YES YES 0.5909% 4142307	YES YES 0.5858% 4142307	YES YES 0.5787% 4142307

Panel B:	Rate g	gap based	on maturing	WMPs'	$\operatorname{returns}$
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Panel C: Rate gap based on newly issued WMPs' benchmark returns

	(1)	(2)	(3)	(4)	(5)
			$Prepay_{t+1 \to t+0}$	3	
X =	0.4%	0.7%	1%	1.3%	1.6%
$Max(RateGap_NewlyIssuedWMP, X)$	$\begin{array}{c} 0.0076^{***} \\ (17.12) \end{array}$	$\begin{array}{c} 0.0083^{***} \\ (15.85) \end{array}$	$\begin{array}{c} 0.0097^{***} \\ (20.27) \end{array}$	$\begin{array}{c} 0.0109^{***} \\ (19.14) \end{array}$	$\begin{array}{c} 0.0116^{***} \\ (17.94) \end{array}$
Controls City-Time FE Within R^2 Obs.	YES YES 0.5700% 4142307	YES YES 0.5811% 4142307	YES YES 0.5930% 4142307	YES YES 0.5916% 4142307	YES YES 0.5869% 4142307

Panel D: Rate gap based on cash-like WMPs' returns

	(1)	(2)	(3)	(4)	(5)
		-	$Prepay_{t+1 \to t+1}$	6	
X =	1.4%	1.7%	2%	2.3%	2.6%
$Max(RateGap_CashLikeWMP, X)$	0.0052^{***} (15.41)	0.0051^{***} (18.44)	0.0054^{***} (19.31)	0.0049^{***} (16.63)	0.0048^{***} (12.87)
Controls City-Time FE Within R^2 Obs.	YES YES 0.5638% 4142307	YES YES 0.5730% 4142307	$\begin{array}{c} {\rm YES} \\ {\rm YES} \\ 0.5905\% \\ 4142307 \end{array}$	YES YES 0.5837% 4142307	YES YES 0.5759% 4142307

Table 4: Interest rate gaps, borrower 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. $Max(RateGap, 0)_{i,t}$ equals the greater value of $RateGap_{i,t}$ and zero. $HighChar_{i,t}$ 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 ranks in the top 30% of the sample, and zero otherwise. $HighEduc_i$ equals one if individual *i* has a degree higher than a bachelor's, and zero otherwise. $HighCreditScore_{i,t}$ equals one if individual *i*'s credit score ranks in the top 30% of the sample, and zero otherwise. All control variables are the same as those in Table 2 and defined in Appendix A. We include 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.

Characteristic =	(1) AUM	(2) Education	(3) CreditScore
$Max(RateGap, 0) \times HighChar$	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%
Obs.	4142307	4142307	4142307

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 assets under management (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). After $Prepay_{i,t}$ is a dummy variable equal to one if individual *i* has made at least one prepayment before month t, and zero otherwise. All control variables are the same as those in Table 2, except in columns (1) and (2), where individuals' AUM is excluded as a control variable. We include individual 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*** (-116.49)	-0.7214*** (-108.35)	-0.0206*** (-2.65)
Controls Individual FE City-Time FE Within R^2 Obs.	YES YES YES 0.69% 5344676	YES YES YES 0.60% 5344676	YES YES 0.17% 1026503

Table 6: A quasi-natural policy experiment

This table examines the impacts of the policy intervention in 2023. Panel A presents the policy's impact on mortgage prepayment behaviors and Panel B presents its impact on household consumption. In Panel A, the dependent variable, $Prepay_{i,t}$, is a dummy variable equal to one if individual *i* prepays their mortgage in month *t*, and zero otherwise. In Panel B, the dependent variable, $Log(Consumption_{i,t})$, is the natural logarithm of individual *i*'s bank card consumption in month *t*. $Treat_i$ is a dummy variable equal to one if individual *i* qualifies for the interest rate reduction, and zero otherwise. $Post_t$ equals one if month *t* is in or after September 2023, and zero otherwise. Individual-level control variables include individual *i*'s loanto-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 individual 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.

Panel A: Prepayment		
	(1)	(2)
	Pre	epay
$Treat \times Post$	-0.005***	-0.005***
	(-5.68)	(-5.76)
Controls	NO	YES
Individual FE	YES	YES
City-Time FE	YES	YES
Within R^2	0.01%	1.19%
Obs.	13444263	13444263
Panel B: Consumption		
	(1)	(2)
	Log(Const	sumption)
Treast y Dest	0.0067**	0.0000***
$1 reat \times Post$	(0,000)	(0.70)
	(2.98)	(2.72)
Controls	NO	YES
Individual FE	YES	YES
City-Time FE	YES	YES
Within R^2	0.00%	3.00%
Obs.	5924701	5924701

Table 7: Frac > 0 and mortgage prepayments at the city level

This table presents the effects of interest rate gaps on prepayments at the city level. We follow Berger et al. (2021) and use $Frac > X_{c,t}$ as the key independent variable. $Frac > X_{c,t}$ is the fraction of city c's existing mortgages with interest rates higher than LPR + X in month t. We use five values for X: -0.6%, -0.3%, 0, 0.3%, and 0.6%. The dependent variable, $PrepayCount_{c,t+1\to t+6}$, is the sum of the monthly percentages of prepayments in total mortgage repayments for city c between months t+1 and t+6. 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 include city fixed effects and 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)	(2)	(3)	(4)	(5)
		Pr	$repayCount_{t+1 \rightarrow t}$	+6	
X=	0%	-0.6%	-0.3%	0.3%	0.6%
Frac > X	0.0468^{***} (5.78)	0.0665^{***} (9.49)	$\begin{array}{c} 0.0414^{***} \\ (6.69) \end{array}$	0.0122^{***} (2.86)	0.0036 (1.28)
Controls	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Within \mathbb{R}^2	4.41%	2.73%	3.30%	1.76%	1.39%
Obs.	12950	12950	12950	12950	12950

Table 8: 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 cfor month t-1. Control variables are consistent with those in Table 7. We include city fixed effects and time fixed effects. Column (3) presents the results of the OLS regression of consumption growth on prepayment ratios. The sample period 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
	$PrepayCount_t$	$\Delta Consumption_{t+1\to t+6}$	$\Delta Consumption_{t+1 \to t+6}$
$Frac > \theta_{t-1}$	0.0137^{***} (5.32)		
$PrepayCount_t$		-8.4770*** (-6.49)	-3.6741*** (-6.92)
F-Stat	28.30		
Controls	YES	YES	YES
City FE	YES	YES	YES
Time FE	YES	YES	YES
Within \mathbb{R}^2	3.37%	1.24%	4.13%
Obs.	6426	6426	6426

Table 9: 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, $\Delta ConsumptionEssn_{c,t+1\to t+6}$ ($\Delta ConsumptionDisc_{c,t+1\to t+6}$) is the average growth of essential (discretionary) consumption 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, $\Delta ConsumptionS_{c,t+1\to t+6}$ ($\Delta ConsumptionL_{c,t+1\to t+6}$) is the average growth of small (large) consumption in city c between months t + 1 and t + 6. Small (Large) consumption in a city c between months t + 1 and t + 6. Small (Large) consumption in a city c between months t + 1 and t + 6. Small (Large) consumption in a city for a month is the sum of the consumption with values lower (higher) than 1,000 RMB in that city for the month. Control variables are consistent with those in Table 7. We include city fixed effects and time fixed effects. The sample period 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)
	$\Delta Consumption to the construction of the con$	$onEssn_{t+1\rightarrow t+6}$	$\Delta Consumption$	$onDisc_{t+1\rightarrow t+6}$
	IV	OLS	IV	OLS
$PrepayCount_t$	-0.0324 (-0.02)	-1.3782^{***} (-3.03)	-8.4640** (-2.40)	-2.3316*** (-3.82)
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Within \mathbb{R}^2	0.66%	1.09%	0.70%	1.46%
Obs.	6426	6426	6426	6426

Panel B: Mortgage prepayment and small vs. large consumption

	(1)	(2)	(3)	(4)
	$\Delta Consump$	$tionS_{t+1 \to t+6}$	$\Delta Consumpt$	$tionL_{t+1\to t+6}$
	IV	OLS	IV	OLS
Prenau Count.	-0.7749	-1 3470***	-8 5001***	-3 7063***
1 repayeo ana	(-0.65)	(-3.46)	(-3.40)	(-6.92)
Controls	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Within \mathbb{R}^2	0.08%	0.63%	1.23%	4.11%
Obs.	6426	6426	6426	6426

Table 10: 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 among the top 30% 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 7. We include city fixed effects and time fixed effects. The sample period 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) $\Delta Consumption_{t+1,t+6}$	
$HighFrac_{t-1} \times \Delta LPR_t$	0.0793^{**} (2.02)	
Controls City FE Time FE Within R^2 Obs.	YES YES 0.81% 6426	

Variable	Definition
Individual-level variables	
$Prepay_{i,t+1 \to t+6}$	A dummy variable which equals one if individual i either partially or fully prepays their mortgage between months t + 1 and $t + 6$, and zero otherwise.
$Prepay_{i,t}$	A dummy variable which equals one if individual i either partially or fully prepays their mortgage in month t , and zero otherwise.
$PrepayPartial_{i,t+1 \rightarrow t+6}$	A dummy variable which equals one if individual i partially prepays their mortgage between months $t + 1$ and $t + 6$, and zero otherwise.
$PrepayFull_{i,t+1 \to t+6}$	A dummy variable which equals one if individual i fully pre- pays their mortgage between months $t + 1$ and $t + 6$, 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 .
$RateGap_MaturingWMP_{i,t}$	The difference between the mortgage rate of individual i and the average realized return of wealth management products (WMPs) maturing in month t .
$RateGap_CashLikeWMP_{i,t}$	The difference between the mortgage rate of individual i and the average annualized return of cash-like wealth man- agement products (WMPs) in month t .
$RateGap_NewlyIssuedWMP_{i,t}$	The difference between the mortgage rate of individual i and the average benchmark return of newly issued wealth management products (WMPs) in month t .
$Log(Deposit_{i,t})$	The natural logarithm of the deposit of individual i at the bank in month t .
$Log(AUM_{i,t})$	The natural logarithm of the assets under management (AUM) of individual i at the bank in month t .
$Log(Consumption_{i,t})$	The natural logarithm of individual i 's spending using the bank's debit card in month t .
$Age_{i,t}$	The age of the individual i in month t .
$MortgageAge_{i,t}$	The age of the household i 's existing mortgage in month t .

Appendix A. Variables Definition

Variable	Definition
$HighEduc_{i,t}$	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.
$CreditScore_{i,t}$	The bank's internal credit score of individual i in month t .
$LTV_{i,t}$	The ratio of mortgage balance to housing value.
City-level and macro-level variab	bles
$PrepayCount_{c,t}$	The ratio of the number of mortgage prepayments to the
	total number of mortgage repayments in city c for month t .
$PrepayCount_{c,t+1 \to t+6}$	The sum of $PrepayCount$ in city c between months $t + 1$
	and $t + 6$.
$PrepayValue_{c,t+1 \rightarrow t+6}$	The ratio of the mortgage prepayment value to the total
	value of mortgage repayments for city c between months
	t + 1 and $t + 6$.
$M_City_{c,t}$	The average interest rate of existing mortgages in city c for
	month t .
LPR_t	The LPR rate in month t .
$Frac > 0_{c,t}$	The fraction of existing mortgages with interest rates higher
	than LPR in city c for month t .
$RateGap_City_{c,t}$	$M_City - LPR.$
$\Delta Consumption_{c,t+1 \to t+6}$	The average monthly growth of consumption made through
	UnionPay cards in city c between months $t + 1$ and $t + 6$.
$\Delta ConsumptionDisc_{c,t+1\rightarrow t+6}$	The average growth of discretionary consumption made
	through UnionPay cards in city c between months $t+1$ and
	t+6. The discretionary categories include alcohol, to bacco,
	cars, electronic devices, entertainment, and inter-city trans-
	portation.
$\Delta ConsumptionEssn_{c,t+1\to t+6}$	The average growth of essential consumption made through
	UnionPay cards in city c between months $t + 1$ and $t + 1$
	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 consumption in city c be-
	tween months $t + 1$ and $t + 6$. Small consumption in a city
	for a month is defined as the sum of the consumption with
	values lower than 1,000 yuan in that city for the month.

Variable	Definition	
$\Delta Consumption L_{c,t+1 \to t+6}$	The average of growth of large consumption in city c between	
	months $t + 1$ and $t + 6$. Large consumption in a city for a	
	month is defined as the sum of the consumption with values	
	higher than 1,000 yuan in that city for the month.	
$GDPGrowth_{c,t}$	Annual real GDP growth rate of city c .	
$GDPPerCap_{c,t}$	The natural logarithm of GDP per capita of city c .	
CPI_t	The percentage change of the Consumer Price Index relative	
	to the prior month.	
PMI_t	The Purchasing Managers' Index for the month t .	
$LogHousingPrc_{c,t}$	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.	
$\Delta HousingPrc_{c,t}$	The log change of housing price in city c for month t .	

Appendix B. Model

B.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.

$$(w_{i,1} - \frac{M_i p_i}{1 + m_i} - c_{i,1})(1 + r) + w_{i,2} - M_i(1 - p_i) = c_{i,2}$$
$$0 \le p_i \le 1$$
$$w_1 - \frac{M_i p_i}{1 + m_i} - c_{i,1} \ge 0.$$

B.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

$$p_i = \frac{w_{i,1}(1+m_i) - w_{i,2} + M_i}{2M_i},\tag{A1}$$

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

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

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 M(1 + m)

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

• 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

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

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 $w_{i,2} < M_i$

B.3. Discussions

First, from the Equation (A1), conditional on prepayment, the proportion of prepayment p_i increases with the mortgage rate m_i and income $w_{i,1}$.

Second, when the savings return 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 savings return,

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

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 savings return.

Appendix C. Additional Empirical Results

Table A1: Amplified responses of WMP returns to LPR adjustment

This table presents the relationship between WMP returns and the LPR. The WMP returns include the average realized return of WMPs maturing in the current quarter (MaturingWMP), the average benchmark return of newly issued WMPs (NewlyIssuedWMP) and the average return of the cash-like WMPs (CashLikeWMP). The results from the regression of WMP returns onto contemporaneous LPR show that the coefficient before LPR are greater than one. 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.

	(1) MaturingWMP	$(2) \\ Newly Issued WMP$	(3) CashLikeWMP
LPR	1.988***	1.158***	1.244***
	(5.55)	(9.76)	(10.91)
Constant	(-3.17)	(-5.52)	(-5.57)
Within \mathbb{R}^2	67.01%	85.39%	89.08%
Obs.	58	58	58

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 $Prepay_{i,t+1\to t+6}$, 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. $Max(RateGap, 0)_{i,t}$ equals the greater value of $RateGap_{i,t}$ and zero. Control variables are consistent with those in Table 2. All variables are defined in Appendix A. In Panel A, we include city-time fixed effects. In Panel B, we additionally control for individual 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 statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: The dynamics of the relationship between the interest rate gap and prepayments						
Prepay	$(1) \\ t+1$	$(2) \\ t+2$	$(3) \\ t+3$	$(4) \\ t+4$	$(5) \\ t+5$	$(6) \\ t+6$
Max(RateGap, 0)	0.0031^{***} (10.74)	$\begin{array}{c} 0.0033^{***} \\ (11.25) \end{array}$	$\begin{array}{c} 0.0033^{***} \\ (11.03) \end{array}$	$\begin{array}{c} 0.0032^{***} \\ (11.44) \end{array}$	0.0032^{***} (10.91)	0.0031^{***} (10.60)
Controls City-Time FE Within R^2 Obs.	YES YES 0.27% 4142307	YES YES 0.12% 4042032	YES YES 0.10% 3970810	YES YES 0.09% 3870227	YES YES 0.08% 3734290	YES YES 0.08% 3620381

Panel B: Including individual fixed effects

	(1)	(2)	(3)
		$Prepay_{t+1 \to t+6}$	
Max(RateGap, 0)	0.0064^{***} (2.91)	0.0050^{**} (2.12)	0.0062^{***} (2.58)
Controls	NO	YES	YES
Individual FE	YES	YES	YES
Time FE	YES	YES	-
City-Time FE	NO	NO	YES
Within R^2	0.00%	0.59%	0.68%
Obs.	4142307	4142307	4142307

Table A3: Linear analysis of interest rate gaps and mortgage prepayments

	(1)	(2)	(3)	
	$Prepay_{t+1 \rightarrow t+6}$			
RateGap	0.0131^{***} (10.82)	$\begin{array}{c} 0.0154^{***} \\ (14.85) \end{array}$	0.0189^{***} (14.89)	
Controls	NO	YES	YES	
City FE	YES	YES	-	
Time FE	YES	YES	-	
City-Time FE	NO	NO	YES	
Within R^2	0.10%	0.91%	0.51%	
Obs.	4142307	4142307	4142307	

Table A4: A quasi-natural policy experiment: robustness

Obs.

This table presents the robustness test of the impacts of the policy intervention in 2023. In Panel A, 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. In Panel B, the dependent variable, $Log(Consumption)_{i,t}$, is the natural logarithm of individual *i*'s bank card consumption in month *t*. $ReducedRate_i$ is the negative value of the change in mortgage rates for the affected individual *i* (to make the expected sign the same as in Table 6). $Post_t$ equals one if month *t* is after September 2023, and zero otherwise. Control variables are consistent with those in Table 6. All variables are defined in Appendix A. We include individual 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.

Panel A: Prepayment			
	(1)	(2)	
	Pr	epay	
ReducedRate imes Post	-0.009***	-0.009***	
	(-4.81)	(-5.02)	
Controls	NO	YES	
Individual FE	YES	YES	
City-Time FE	YES	YES	
Within \mathbb{R}^2	0.01%	1.19%	
Obs.	13444263	13444263	
Panel B: Consumption			
	(1)	(2)	
	Log(Con	sumption)	
ReducedRate imes Post	0.0322***	0.0319***	
	(5.22)	(5.91)	
Controls	NO	YES	
Individual FE	YES	YES	
City-Time FE	YES	YES	
Within R^2	0.01%	3.00%	

5924701

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Table A5: A quasi-natural policy experiment: partial vs. full prepayments

This table examines the impacts of the policy intervention in 2023 on partial and full prepayment behaviors. *PartialPrepay*_{i,t} is a dummy variable equal to one if individual *i* partially prepays their mortgage in month t, and zero otherwise. *FullPrepay*_{i,t} is a dummy variable equal to one if individual *i* fully prepays their mortgage in month t, and zero otherwise. *Treat*_i equals one if individual *i* qualifies for policy, and zero otherwise. *Post*_t equals one if month t is after September 2023, and zero otherwise. Control variables are consistent with those in Table 6. All variables are defined in Appendix A. We include individual fixed effects and city-time fixed effects. The sample includes all mortgages issued by the bank 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)	(3)	(4)
	Partial Prepay		Full Prepay	
$Treat \times Post$	-0.003*** (-2.85)	-0.004*** (-3.88)	-0.001*** (-3.17)	-0.001** (-2.05)
Controls Individual FE	NO YES	YES YES	NO YES	YES YES
City-Time FE Within R^2 Obs.	$YES \\ 0.01\% \\ 13,444,263$	$YES \\ 0.49\% \\ 13,444,263$	$YES \\ 0.00\% \\ 13,444,263$	$YES \\ 0.97\% \\ 13,444,263$
Table A6: Frac > 0 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. In Panel A, the dependent variable is $PrepayCount_{t+k}$, the percentage of prepayment of all existing mortgages for a specific month t + k, where k ranges from 1 to 6. In Panel B, the dependent variable, $PrepayValue_{c,t+1\to t+6}$, is the ratio of the mortgage prepayment value to the total value of mortgage repayments for city c between months t + 1 and t + 6. $Frac > 0_{c,t}$ is the fraction of existing mortgages with interest rates higher than the LPR in city c for month t. Control variables are consistent with those in Table 7. We include city fixed effects and 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.

Panel A: The dynamics of the relationship between the $Frac > 0$ and prepayments								
	(1)	(2)	(3)	(4)	(5)	(6)		
PrepayCount	t+1	t+2	t+3	t+4	t+5	t+6		
Frac > 0	0.0060^{***} (2.47)	0.0082^{***} (3.82)	$\begin{array}{c} 0.0044^{***} \\ (3.71) \end{array}$	0.0060^{**} (2.33)	0.0045^{*} (1.69)	$0.0025 \\ (1.03)$		
Controls	YES	YES	YES	YES	YES	YES		
City FE	YES	YES	YES	YES	YES	YES		
Time FE	YES	YES	YES	YES	YES	YES		
Within \mathbb{R}^2	0.79%	1.16%	1.17%	0.73%	0.57%	0.33%		
Obs.	12950	12680	12680	12420	12160	11900		

Panel B: Alternative prepayment ratio based on prepayment values

	$(1) Prepay Value_{t+1 \to t+6}$		
Frac > 0	1.0356^{***} (6.10)		
Controls City FE Time FE Within R^2 Obs.	YES YES YES 4.08% 12950		

Table A7: City-level interest rate gaps and mortgage prepayments

This table presents the effects of interest rate gaps on mortgage prepayments at the city level using linear regressions. The dependent variable, $PrepayCount_{c,t+1\rightarrow t+6}$, is the sum of the monthly percentages of prepayments in total mortgage repayments for city c between months t+1 and t+6. $RateGap_City_{c,t}$ is the difference between $M_City_{c,t}$ and LPR_t , where $M_City_{c,t}$ is the average interest rate of existing mortgages in city c for month t. Control variables are consistent with those in Table 7. We include city fixed effects and 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)	(2)	
	$PrepayCount_{t+1 \to t+6}$		
$RateGap_City$	0.0252^{***} (8.25)	$\begin{array}{c} 0.0242^{***} \\ (7.34) \end{array}$	
Controls	NO	YES	
City FE Time FE	YES YES	$\begin{array}{c} \text{YES} \\ \text{YES} \end{array}$	
Within R^2 Obs.	$3.19\% \\ 12950$	$4.04\% \\ 12950$	