Inflation Heterogeneity and Household Financial Decisions: Evidence from Housing Markets

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Abstract

Lower income households have experienced higher inflation since the 2000s. I find that households who experience a rise in inflation (relative to the national inflation) increase borrowing from the mortgage market and holdings of housing assets. Empirically, I identify this effect by exploiting exogenous shocks in exchange rates, leveraging that lower income households spend a greater share of their income on tradable goods. The findings can be explained by that households relocate their savings to markets where real returns are protected from relative inflation. A calibrated general equilibrium model suggests a smaller dispersion in home ownership between income groups but a greater dispersion in welfare, as a result of inflation heterogeneity.

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1. Introduction

Households systematically experience different inflation levels because they persistently consume different baskets of products, whose prices evolve differently over time. In particular, a growing body of research shows that lower income households on average experience higher consumption inflation, compared to higher income households since the 2000s (e.g., Kaplan and Schulhofer-Wohl (2017) and Jaravel (2019)). This inflation heterogeneity can create differences in real returns conditional on the same nominal investment position. The resulting real return heterogeneity should affect household savings and investment decisions. Since Fisher (1933), there has been a substantial effort to understand how national inflation transfers wealth between creditors and borrowers, impacts financial decisions, and affects real aggregates and asset prices.[i] However, limited attention is paid to the heterogeneity in inflation across households and its interactions with financial markets.

This paper studies how inflation heterogeneity across different household groups affects financial decisions. When group-specific inflation rises (relative to the national inflation), theory suggests that households will dissave in markets where real returns are eroded, and save more in markets where real returns are protected from relative inflation spreads. I indeed empirically find that groups of households experiencing a rise in inflation relative to the national average inflation increase borrowing from the mortgage market and holdings of housing assets. To understand the consequences of inflation heterogeneity, I calibrate a general equilibrium model that features a cross-sectional relation between income and inflation and use the model to conduct counterfactual analyses. The model predicts a smaller dispersion in home ownership between income groups but a greater dispersion in welfare, as a result of inflation heterogeneity.

Following Jaravel (2019), I measure relative inflation spreads as the difference between the group-specific inflation and the national average inflation, using the transaction-level Nielsen Consumer Panel data. Relative inflation spreads can alter real returns depending on the market structure. Standardized assets traded in "centralized" markets (e.g., stocks and bonds) are more likely to offer the same nominal return to all investors and, thus, lead to differences in real returns due to cross-sectional inflation heterogeneity. Notably, the conforming mortgage market has been documented as highly standardized with little

[i] For example, Fama (1981), Doepke and Schneider (2006), Gomes et al. (2016), Corhay and Tong (2021), etc.

price heterogeneity (Hurst et al. (2016)). In some other markets, however, relative inflation spreads do not directly affect real returns. The most prominent example is the housing market. Conditional on owning a house, relative inflation spreads will not directly change the size and quality of the house, and therefore the utility flow from housing will be unaffected. Furthermore, housing markets are "segmented" across income groups, which is known as geographic income segregation, documented by Reardon and Bischoff (2011), Guerrieri et al. (2013), and Landvoigt et al. (2015). Given this segmentation feature, nominal rent and house prices can potentially adjust for relative inflation spreads and shield the real returns away from the direct effect of inflation heterogeneity.

Consider a scenario where the relative inflation spread rises for a specific group of households. Real returns in "centralized" markets drop, which makes those markets less attractive places to save. Instead, households prefer to move their savings into the "segmented" housing markets where real returns are protected from relative inflation spreads. Taking it one step further, households would like to borrow from "centralized" markets because of lowered real borrowing costs and invest in the "segmented" housing markets to mitigate against relative inflation spreads. Therefore, it is reasonable to expect that inflation heterogeneity has a potent effect in mortgage-financed housing decisions because of the combination of a "centralized" and "standardized" mortgage liability and a "segmented" and "real" housing asset. Furthermore, home purchase and mortgage borrowing are the most prominent financial decisions that typical US households make. Finally, rich data with detailed information from the mortgage market allow me to carefully design empirical investigations of the causal impact of inflation heterogeneity on household behavior.

I first document the association between relative inflation spreads and mortgage activity in the data. Consistent with the above prediction, I find a positive correlation between relative inflation spreads and mortgage borrowing, using census tract by year level data from HMDA. In addition, using individual household-level data from American Community Survey, I also find home ownership increases when relative inflation spreads rise. This indicates that the increase in mortgage borrowing is associated with actual home purchases by households in the corresponding group. All of the above results are robust in the subsample after the 2008-2009 Financial Crisis, which suggests that the housing boom and bust do not drive the documented patterns. Last but not least, the results remain consistent for a battery of alternative inflation measures.

To address endogeneity concerns, I employ two identification strategies. In particular, I use the Chinese Yuan (RMB) to US Dollar (USD) exchange rate as an instrumental variable for inflation heterogeneity across income groups and the 2005 Chinese Yuan reform as an unexpected shock. Both empirical strategies leverage the literature that documents that tradable goods constitute a more significant share in the consumption baskets of lower income households, and trade shocks have greater impacts on the prices of lower end products (Fajgelbaum and Khandelwal (2016), Cravino and Levchenko (2017), Jaravel and Sager (2019)). As a result, exchange rate movements disproportionately affect inflation rates of lower income households.[ii] China is responsible for the largest share of US imports since 2007. Consistent with the previous literature, I document that there is a positive and robust correlation between RMB appreciation against USD and US inflation heterogeneity across income groups. Using the appreciation of RMB against USD as an instrumental variable, I find a one percentage point increase in relative inflation spreads leads to an increase in home ownership by nine percentage points.

In addition, on 21 July 2005, China abandoned its fixed exchange rate system.[iii] RMB immediately appreciated by 2.1% against USD within one day, and further appreciated by nearly 20% against USD over the following year. The exact timing of this reform was unexpected by the market (Frankel and Wei (2007)). I find that the unexpected RMB appreciation is associated with a widened gap in both realized inflation and inflation expectations between the low and high income US households. Moreover, there is no effect on income expectation and employment expectations. Consistent with previous findings, I document that mortgage borrowing by the low income households increased after the RMB reform.

To conduct counterfactual analyses, I calibrate a model that captures the general equilibrium effects of inflation heterogeneity across income groups on asset prices, the cross-section of housing consumption, and household welfare. The model features an endowment economy that consists of overlapping generations and heterogeneous income groups with idiosyncratic shocks. In the model, households endogenously make home ownership, savings, mortgage, and consumption decisions. The equilibrium national interest rate and "segmented" house prices are determined by market clear conditions.

The model quantitatively matches the cross-sectional dispersion in home ownership,

[ii] For example, Cravino and Levchenko (2017) shows currency devaluation in Mexico increased the inflation rate for low-income households more. Jaravel and Sager (2019) find the magnitude of the domestic price response is 5 times larger for product categories that cater to the lower-income households.

[iii] From 1997 to 2005, the Chinese government maintained a peg of 8.27 RMB per USD.

house price to income ratio, and house size differences between low income and high income households. Using the model, I then ask what would happen in the mortgage and housing markets in the absence of inflation heterogeneity. I find that higher relative inflation spreads push lower income households to borrow from the mortgage market and invest into “segmented” housing markets, which leads a smaller dispersion in home ownership across income groups. However, it also creates a thicker left tail distribution of housing consumption, i.e., some households who can not afford to buy a house are forced to rent a smaller one due to higher house prices in their segment. Last, the model suggests a larger dispersion in welfare across income groups. Lower income households are worse off because of lower real income and lower real return from savings, as housing assets can not fully mitigate the effect of relative inflation spreads.

The paper is organized as follows: Section 2 discusses the related literature, Section 3 presents a conceptual framework and the prediction, Section 4 shows consistent empirical patterns from the data, Section 5 introduces two identification strategies, Section 6 calibrates a structural model for counter-factual analyses, and Section 7 concludes.

2. Literature

This paper connects the growing literature on inflation heterogeneity across income groups to the literature on inflation and household financial decisions. Powered by newly available granular household shopping data, Kaplan and Schulhofer-Wohl (2017), Jaravel (2019), and Argente and Lee (2020) show lower income households systematically experience higher inflation levels between 2004 and 2015. Jaravel (2019) further finds a similar pattern exists in a longer period from 1955 to 2015 using the merged CEX-CPI data. Meanwhile, there is a rich body of studies on how household inflation experiences and expectations affect financial choices. Using data on inflation expectations from the Michigan Survey of Consumers, Malmendier and Nagel (2016) find differences in household inflation experiences strongly predict differences in inflation expectations, and higher experience-induced inflation expectations lead to more borrowing, especially from the mortgage market. DAcunto et al. (2021) document that consumers update their inflation expectations from their grocery shopping experiences, although suffering from behavioral biases. Vellekoop and Wiederholt (2019) directly link survey data on quantitative inflation expectations to administrative data on income and wealth, and they document that households with higher inflation expectations consume more durable products like cars. My paper contributes to the literature by showing how the systematic inflation heterogeneity across income groups matters for household financial decisions. I find households increase borrowing from the mortgage market and holdings of housing assets to mitigate higher relative inflation by "exploiting" real return differences across markets caused by the inflation heterogeneity.

This paper also speaks to the literature on the interaction between inflation and the financial markets. Because many debt-like financial contracts are written in nominal terms, inflation shocks will lead to wealth transfer between creditors and borrowers, known as the Fisher channel since Fisher (1933). Doepke and Schneider (2006) measure the balance sheet's inflation exposure of various groups of households and investors in the US. The differential balance sheet exposure has real effects on the aggregate economy when households have different marginal propensities to consumption, as discussed by Auclert (2019). On the production side, Kang and Pflueger (2015) and Gomes et al. (2016) show that unanticipated inflation changes firms' real burden of debt and future investment and production decisions via a sticky leverage channel. Corhay and Tong (2021) further consider the financial intermediation sector and find higher inflation hurts intermediaries' balance sheet, leading to a contraction in credit. My paper instead emphasizes a different scenario where households intrinsically experience different inflation levels. I show that the differences in inflation levels can affect household financial decisions. I further argue that inflation heterogeneity matters for asset prices and the cross-sectional dispersion of housing consumption across income groups.

3. A Conceptual Framework

This section presents a conceptual framework to illustrate how inflation spreads (relative to the national inflation) can interact with different financial markets, change real returns, and therefore affect household financial decisions.

3.1 Inflation Heterogeneity and Two Types of Financial Markets

Households systematically experience different inflation levels because they persistently consume different baskets of products, whose prices evolve differently over time. In particular, a growing body of research shows that lower income households on average experience higher consumption inflation, compared to higher income households since the 2000s (e.g., Kaplan and Schulhofer-Wohl (2017) and Jaravel (2019)). This inflation heterogeneity can lead to heterogeneity in real returns given the same nominal position, depending on the market structure. In this paper, conceptually, I classify financial markets into two groups based on whether real returns from those markets are directly affected by inflation heterogeneity or not.

In the first category of financial markets, inflation heterogeneity directly creates differences in real returns. The first category includes "centralized" markets where "standardized" assets are traded. Only one price exists for each asset at a given time. Conditional on the same nominal position, a "standardized " asset from a "centralized" market is more likely to offer the same nominal return to all households, regardless of the specific inflation processes that households face. Examples are bonds, stocks, and other publicly traded standardized financial instruments. Important to this paper, the conforming mortgage market has been documented as highly standardized with little price heterogeneity (Hurst et al. (2016)).

In the second category of financial markets, real returns are not directly affected by inflation heterogeneity. First of all, some assets in nature deliver real payoff flows. The most prominent example is the housing market. Conditional on owning a house, the real house size you enjoy each period will not be directly reduced or increased by your inflation spread, and therefore the utility flow from housing will be unaffected. Furthermore, housing markets are "segmented" across income groups, which is known as geographic income segregation, documented by Reardon and Bischoff (2011), Guerrieri et al. (2013), and Landvoigt et al. (2015). Given this segmentation feature, nominal rent and house prices can potentially adjust for relative inflation spreads and shield real returns away from the direct effect of inflation heterogeneity.

3.2 A Toy Model and the Empirical Prediction

Motivated by the previous patterns, I explore the theoretical implications of inflation heterogeneity on household financial decisions in a simple partial equilibrium framework.

3.2.1 Environment

Consider a household lives for two periods, receives nominal endowments w in the first period, and consumes retail good c_t and housing service h_t. The national inflation is assumed to be zero. The price of retail goods exogenously experiences a relative inflation spread π_j between the first and second period. Household's utility from a bundle of $\{c, h\}$ is

$$u(c,h) = \frac{\left(c^{\theta} \cdot h^{1-\theta}\right)^{1-\gamma}}{1-\gamma}$$

The household can save via a "centralized" bond market and a "segmented" housing market. The "centralized" bond market provides one-period nominal bonds with a risk-free return R_f. The household can also buy houses with the price of P_j in the first period, and the household is allowed to sell the house and consume using the home value in the second period. For simplicity, I assume rent r is determined in a competitive rental market, where $r = P \cdot (R_f - 1)$.[iv]

To maximize expected utility, the household chooses savings s in the bond market and house size h_2 in the housing market, as well as the first period retail consumption c_1 and rental house size h_1.

$$\max_{c_1,h_1,s,h_2} = u(c_1,h_1) + \beta \cdot u(c_2,h_2)$$

subject to budget constraints

$$c_1 + r \cdot h_1 = w - s - P \cdot h_2,$$
$$e^{\pi_j} \cdot c_2 = s \cdot R_f + P \cdot h_2$$

3.2.2 Partial Equilibria and The Empirical Prediction

Figure 1 shows the effect of relative inflation spreads π_j on household savings choices in the housing market and the bond market. Figures (a) and (b) plot the scenario when $\gamma = 5$.[v] As π_j rises, figures (a) shows household's savings in the housing market increase , meanwhile figures (b) shows household's savings the in bond assets decrease. In combination, the household moves her portfolio from the bond market to the housing market.

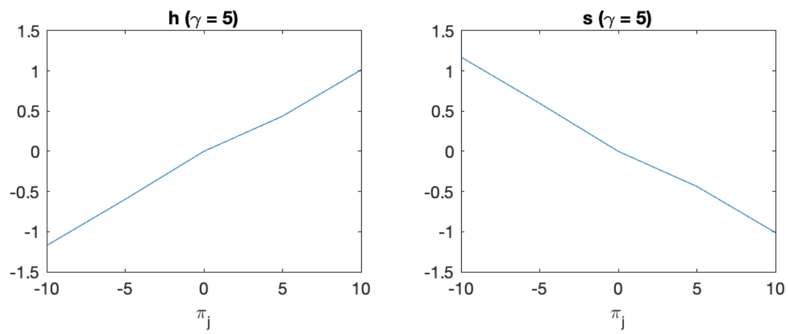
The intuition behind the above reallocation is that, when π_j increases, the real value of the same nominal savings in the second period decreases. With the elasticity of in-

[iv]I assume an exogenous fixed housing price, no decapitation and property tax in this partial equilibrium toy model. These assumptions will be relaxed in Section 6. The competitive rental market assumption follows İmrohoroğlu et al. (2018).

[v]The assumption of a coefficient of relative risk aversion $\gamma > 1$ is typical in the macro-housing literature (e.g. Davis and Ortalo-Magné (2011) and Cocco et al. (2005)).

Figure 1: **Inflation Heterogeneity and Household Portfolio Allocation**

This figure shows the effect of relative inflation spreads π_j on household's savings choices in the housing market and the bond market. Figures (a) and (b) plot the scenario when $\gamma = 5$. The x-axes of all subplots are relative inflation spreads π_j, in percentage points. The y-axes are also in percentage points, relative to the case when $\pi_j = 0$. As π_j rises, figures (a) shows household savings in the housing market increase, meanwhile figures (b) shows household savings (borrowing) in the bond market decrease (increases).



tertemporal substitution $\frac{1}{\gamma} < 1$, the household will save more in nominal terms to smooth real consumption in the second period. However, saving via the "centralized" bond market becomes less attractive, as real returns are reduced by higher relative inflation spreads. Take one step further, if possible, households would like to borrow from the bond market, because the real borrowing cost becomes lower. At the same time, "segmented" housing assets gain an advantage because the real return of owning a house is protected from relative inflation spreads. Conditional on owning a house, relative inflation spreads will not directly change the size and quality of the house, and therefore the utility flow from housing will be unaffected.[vi]

Housing and mortgage markets are the ideal places to test the model's prediction. First, the conforming mortgage market has been documented by the literature as "centralized" and "standardized" (more discussion in Section 4.3.1) and housing markets are "real" and "segmented" (more discussion in Section 4.3.2). Therefore, it is reasonable to expect that inflation heterogeneity has a potent effect in mortgage-financed housing decisions because of the combination of a "centralized" and "standardized" mortgage lia-

[vi]Furthermore, in Section 6, I will use a general equilibrium model with endogenous house prices and segmented housing markets to show that nominal rent and house prices increase with π_j, which further shields housing real returns away from the direct effect of inflation heterogeneity.

bility and a "segmented" and "real" housing asset. Second, housings (mortgages) are the largest assets (liabilities) for US households across all income quintiles (as indicated by Figure IA.6, Figure IA.7a, and Figure IA.7b), and home purchase and mortgage borrowing are the most prominent financial decisions that a typical household makes. Finally, rich data with detailed information from the mortgage market allow me to carefully design empirical investigations of the causal impact of inflation heterogeneity on household behavior.

In sum, the model predicts that when relative inflation spreads rise, households will borrow more from the mortgage market to finance their investments in the "segmented" housing market.

Hypothesis. *When the relative inflation spread π_j rises, households will increase mortgage borrowings and housing investments.*

4. The Empirical Setting and Preliminary Evidence

This section presents data, measures, and consistent empirical patterns with the conceptual framework discussed in Section 3. The inflation heterogeneity can exist in many other cross-sectional dimensions. In this paper, I focus on the heterogeneity across the income distribution for empirical reasons (more discussion in Section 5.1). Consistent with the conceptual prediction, I find that households increases mortgage borrowings and housing investments, when they experience higher relative inflation spreads.

4.1 Data

This study Nielsen Consumer Panel to estimate relative inflation spreads. Home Mortgage Disclosure Act data (HMDA) and Zillow's Assessor and Real Estate Database (ZTRAX) are used to measure household mortgage borrowing and housing transactions. I uses American Community Survey for individual-level home ownership, mortgage status, income, rent, home value, and geographic and demographic characteristics. Michigan Surveys of Consumers are used to measure household inflation expectations. As the Nielsen Consumer Panel only starts from 2004, the sample period in this paper is between 2005 and 2019.

4.2 Inflation Heterogeneity Across Income Groups

Lower income households and higher income households spend not only differently across broad categories (food, energy, education, health, and etc.), but also across quality ladders within a given product type. Using newly available granular household shopping data, a growing body of research shows there exists systematic and persistent inflation heterogeneity across income groups. In particular, Kaplan and Schulhofer-Wohl (2017) and Jaravel (2019) find that lower income households on average experience higher consumption inflation, compared to higher income households since the 2000s.

The Nielsen Consumer Panel records consumption starting from 2004 for a rotating panel of about 40,000 households, who are instructed to scan and input the price and quantity of any product they purchase that has a barcode, typically from retail stores. The Nielsen Consumer Panel data have detailed information on household characteristics such as income, age, and education. In the Nielsen Consumer Panel data, a product k is defined by its barcode, which allows me to compare the prices of the same product in two periods. Following the method used in Jaravel (2019), I calculate the year-to-year relative inflation spreads of an income group as:

$$\pi_{j,t} = \Pi_{k=1}^{n} \left(\frac{p_{k,t}^{j}}{p_{k,t-1}^{j}} \right)^{\frac{s_{k,t-1}^{j}+s_{k,t}^{j}}{2}} - \pi_t,$$

where j indexes income groups, k products, and t time; $s_{k,t}^{j}$ is the spending share and $p_{k,t}^{j}$ is the average price paid by the income group j on product k in year t. Note that the spending shares $s_{k,t}^{j}$ are updated each year to better approximate the changes in consumption baskets. π_t is the national average inflation across income groups estimated with the same method. Using the same method but aggregating consumption basket for each month rather than each year, I can also estimate the month-to-month relative inflation spread for income group j. Alternative inflation measures are examined in Table IA.4 and IA.7 as robustness checks.

Micro-level survey data suggest that households have a consistent perception of inflation heterogeneity in their inflation expectations. This question is important as many studies demonstrates the crucial role that inflation expectation plays in household financial decisions, for example, Malmendier and Nagel (2016); Vellekoop and Wiederholt (2019); DAcunto et al. (2021). Plotting the average one year forward inflation expectation by household income groups, Figure IA.3a shows that the low income households always expect inflation to be higher than what the high income households expect, following the same pattern of the realized inflation heterogeneity documented by Jaravel (2019) and Kaplan and Schulhofer-Wohl (2017).

4.3 Inflation Heterogeneity and Mortgage and Housing Markets

In Section 3, I group financial markets into two types based on how real returns are affected by inflation heterogeneity. I emphasize the mortgage market, especially conforming loans, as "centralized" and "standardized", where real returns are directly changed by relative inflation spreads, and housing markets as "segmented" and "real", where real returns are protected from the direct impact of inflation heterogeneity. Consistent empirical evidence that supports the above classifications is discussed as follows.

4.3.1 The Conforming Mortgage Market

Important to this paper, the mortgage market, especially the conforming mortgage market, has been documented as highly standardized with little price heterogeneity (Hurst et al. (2016)). That is, nominal borrowing costs do not fully incorporate group-specific characteristics.

I confirm that mortgage rates also do not adjust for relative inflation spreads across income groups, using GSE conforming loan performance data. Figure IA.4a and Figure IA.4b plot relative inflation spreads and nominal mortgage rate spreads, with and without adjusting for predictable default risks, for each income quintile at each year. Default risks are predicted following Hurst et al. (2016). If mortgage rates one-to-one reflect relative inflation spreads, we should expect a 45 degree line in both Figure IA.4a and Figure IA.4b. However, data suggest that on average, relative mortgage rate spreads are only 0.17 percentage point higher when relative inflation spreads are 1 percentage point higher. It indicates that, households experiencing higher relative inflation spreads pay a lower real mortgage rate than others.

4.3.2 Geographic Income Segregation and "Segmented" Housing Markets

On the other hand, housing markets have been documented as "segmented" across income groups. There is a growing discussion on the increasing geographic income segregation, i.e., low income households and high income households more and more live in different neighborhoods within a metropolitan area or a county, for example by Reardon and Bischoff (2011). Furthermore, this increasing geographic income segregation leads to different processes of nominal house prices across income groups, as shown by Guerrieri et al. (2013).

Consistent with the literature, I find that properties in low (high) income areas are more likely to be purchased by similarly low (high) income households, using mortgage level HMDA data between 2005 and 2019. For a given mortgage, HMDA allows me to identify the income quintile that the buyer belongs to and the income quintile of the average household in the census tract where the property locates at. Figure IA.5 and Table IA.1 display the distribution of buyers' income quintiles by census tract income quintiles where properties locate at. In the bottom income quintile census tract, 83% of properties are purchased by households from the bottom two income quintiles. In the top income quintile census tract, 82% of properties are purchased by households from the top two income quintiles. This segmentation shows that houses are "segmented" assets as they are mostly held within similar income groups.

4.4 Evidence from Mortgage Borrowings

To test whether higher relative inflation spreads can increase mortgage borrowing and housing investments, as predicted in Section 3.2.2, I first run the following regression on a census tract by year panel constructed using the HMDA data:

$$\ln(Num_{k,j,c,t} + 1) = \beta \cdot \pi_{j,t} + \gamma \cdot X_{k,j,c,t} + \psi_{c,t} + \eta_k + \epsilon_{k,j,c,t}, \quad (1)$$

where $Num_{k,j,c,t}$ is the number of mortgages originated at census tract k in year t for home purchase purpose. The average borrower in census tract k belongs to income quintile j in year t. And $\pi_{j,t}$ is the relative inflation spread of the income quintile j in year t. $\psi_{c,t}$ are the county by year fixed effects, and η_k are the census tract fixed effects. $X_{k,j,c,t}$ are other control variables of census tract k, including the log of median income, Zillow home value index at the census tract, 1-year local housing market return, 5-year housing market return, 1-year local rent growth, and local rent level.

By including year by county fixed effects, I compare a census tract with other census tracts in the same county in the same year, which allows nonparametrically absorbing county-level time-varying economic variations, for example, changes in local labor markets and local credit markets. Moreover, I also control for short term and long term interest rates and national inflation rates, and allow heterogeneous sensitivities to those variables across income groups. I use census tract fixed effects to control time-invariant census tract level characteristics. 1-year local housing market return and 5-year local housing market return are used to capture the short term momentum and the long term reversal in local housing markets caused by either extrapolative beliefs (Armona et al. (2019), and Kuchler and Zafar (2019)) or improved home equity and relaxed collateral or liquidity constraints (Fuster and Zafar (2016)).

Consistent with the prediction from Section 3.2.2, Figure 2a and Table IA.2 show that, when experiencing higher relative inflation spreads, households in the corresponding income group increase mortgage borrowings for home purchase compared to the other households in the same county in the same year. This positive association between relative inflation spreads and mortgage borrowing is robust across various specifications. In column 5 of Table IA.2, one percentage point increase in the relative inflation spread is associated with a 0.09 increase in log one plus the number of mortgage borrowing by households.

It is reasonable to suspect whether the above results are driven by the subprime mortgage crisis between 2007 and 2009, either through a household demand channel as shown by Mian and Sufi (2009, 2011), or a financial system supply channel as shown by Ramcharan et al. (2016). To address this question, I run the same specification using the subsample starting from 2010. The results are shown in Table IA.3 and are consistent with the full sample findings.

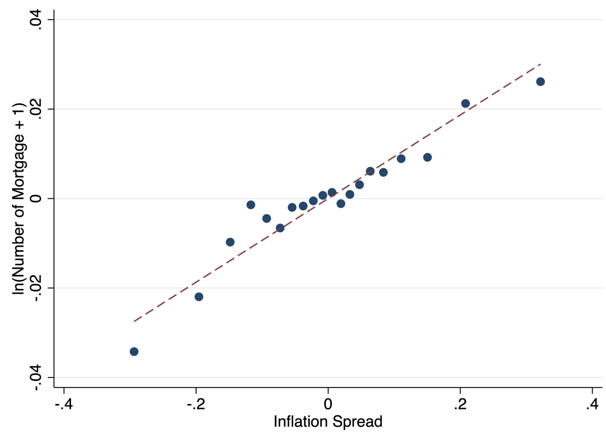
4.5 Evidence from Home Ownership

Section 4.3.2 shows housing markets are largely "segemented" in the sense that households in income quintile j typically buy properties at census tracts in the same or similar income quintile. However, it is still possible that buyers from very different income quintiles drive the increase in number of mortgages originated for home purchase purpose. To address this concern, I run the second regression using household level American Community Survey data:

$$\text{Home Ownership}_{i,j,k,c,t} = \beta \cdot \pi_{j,t} + \gamma \cdot X_{i,j,k,c,t} + \psi_{c,t} + \eta_k + \epsilon_{i,j,k,c,t} \tag{2}$$

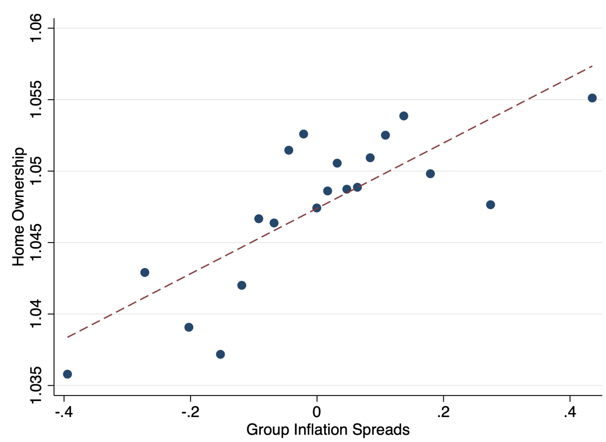
Figure 2: **Mortgage Borrowing, Home Ownership, and Relative Inflation Spread**

Figure (a) shows the correlation between log of one plus the number of mortgages originated and relative inflation spreads at census tract by year level, using the specification 1 with data from HMDA. Figure (b) shows the correlation between home ownership and relative inflation spreads at household level, using the specification 2 with data from American Community Survey data.



(a) Mortgage Borrowing

Data: HMDA



(b) Home Ownership

Data: American Community Survey

where Home Ownership$_{i,j,k,t}$ is a dummy variable that equals to one if household i reports herself as a homeowner. $\pi_{j,t}$ is the relative inflation spread of the income quintile j that household i belongs to in year t. $\psi_{c,t}$ are the county by year fixed effects, and η_k are the public use micro area (PUMA) fixed effects. $X_{i,j,k,c,t}$ are other control variables, including the log of household income, PUMA home value level, 1-year PUMA home value appreciation, 1-year PUMA rent growth, and PUMA rent level. I also control for short term and long term interest rates and national inflation rates and allow heterogeneous sensitivities to those variables across income groups.

Figure 2b and Table IA.5 show that home ownership is also positively correlated with the relative inflation spread $\pi_{j,t}$. A one percentage point increase in relative inflation spreads is associated with a three percentage points increase in home ownership in the corresponding income group. The same pattern holds using the subsample after the Financial crisis, both qualitatively and quantitatively, as shown in Table IA.6.

Taken together, the results from Table IA.2 and Table IA.5 are consistent with the prediction that households increase mortgage borrowings to finance home purchases when relative inflation spreads rise.

5. Identification using Exchange Rate Movements

Obviously, I should be careful to interpret the above results because of endogeneity concerns. For example, if a higher relative nominal income growth causes both a higher relative inflation and an increase in home purchase, the documented positive correlation between relative inflation spreads and housing investments are misleading and driven by an omitted variable problem.

To address endogeneity concerns, I employ two identification strategies. In particular, I use the Chinese Yuan (RMB) to US Dollar (USD) exchange rate as an instrumental variable for US inflation heterogeneity across income groups and the 2005 Chinese Yuan reform as an unexpected shock.[vii] Both method leverages the literature that documents 1) tradable goods constitute a more significant share in the consumption baskets of lower income households and 2) trade shocks have greater impacts on the prices of lower end products (e.g. Fajgelbaum and Khandelwal (2016), Cravino and Levchenko (2017), and Jaravel and Sager (2019)). As a result, exchange rate movements affect the price of con-

[vii] An example in the literature using exchange rate movements as instrumental variables is Bastos et al. (2018)

sumption baskets of the low income households more than they do for the high income households. Cravino and Levchenko (2017) show the domestic currency devaluation in Mexico disproportionally increased the inflation rate for lower income households. China is responsible for the largest share of US imports since 2007. In 2017, the total US value of imports from China is $505 trillion dollars,[viii] which is 3.8% of the $13,333 trillion dollars total US personal spending.[ix] Furthermore, Jaravel and Sager (2019) find that the US domestic prices response stronger to the China trade shock in product categories that cater to lower income households. One percentage point increase in China's import penetration leads to a 4.3% (0.9%) decline in prices for a product targeting lower (higher) income households.

5.1 Chinese Yuan Exchange Rate as The Instrumental Variable

I first use the appreciation of RMB against USD as an instrument for US inflation heterogeneity across income groups. The IV estimations are all consistent with the OLS estimations qualitatively and stronger quantitatively. The robust consistency suggests a causal effect of inflation heterogeneity on household mortgage and housing investments.

5.1.1 The Relevance Condition

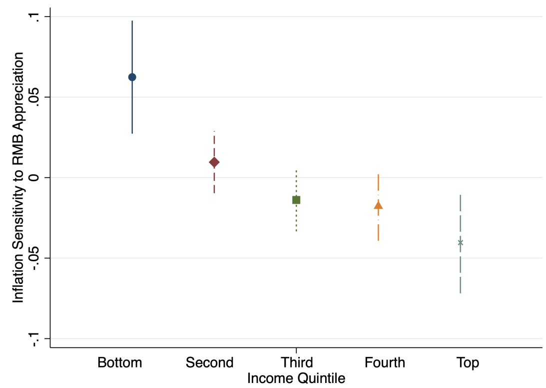
Motivated by the previous literature, I expect the exchange rate movements of the RMB against USD will disproportionally affect the relative inflation spread of lower income US households. Indeed, I find the relative inflation spread of the bottom income quintile shows the strongest and most positive correlation with RMB Appreciation against USD. Furthermore, the estimated correlations decline monotonically for higher income quintiles. Figure 3a shows this pattern by plotting the estimated coefficients of regressing relative inflation spreads on RMB appreciation against USD for each income quintile. Furthermore, Figure 3b reports the month-to-month RMB appreciation against USD and the difference in the month-to-month inflation between the bottom income households and the top income households. The correlation between RMB appreciation and the inflation gap is 0.45. In addition, Figure IA.8 shows the difference in the 1-year forward inflation expectation between the bottom income households and the top income households from

[viii] Data source: United States Census Bureau

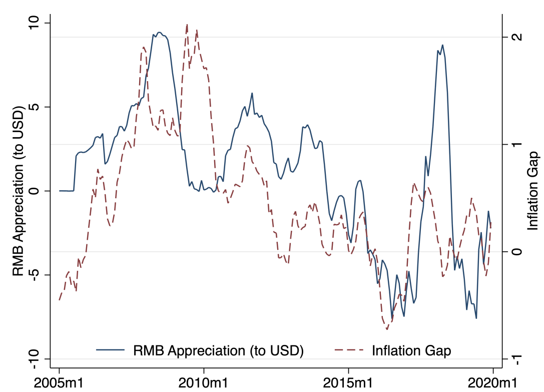
[ix] Data source: US Bureau of Economic Analysis

Figure 3: **US Inflation Heterogeneity and Chinese Yuan Exchange Rate**

Figure (a) plots the coefficients of regressing relative inflation spreads on Chinese Yuan (RMB) Appreciation against US Dollar (USD) by income quintiles. The relative inflation spread of the bottom income quintile shows the strongest and most positive correlation with RMB against USD. And the estimated correlations decline monotonically for higher income quintiles. Figure (b) reports the month-to-month RMB appreciation against USD and the difference in month-to-month inflation rates between the bottom and top income US households. The correlation between RMB appreciation and the inflation gap is 0.45.



(a) Regression Coefficients of Relative Inflation Spreads on RMB Appreciation



(b) Correlation Between Inflation Gap and RMB Appreciation the Michigan Survey of Consumers. The correlation between RMB appreciation and the 1-year forward inflation expectation gap is 0.53.

To formally test the relevance condition, I regress the time series of RMB appreciation on the inflation difference between the bottom and top income US households, $\text{Inflation Gap}_t = \pi_{1,t} - \pi_{5,t}$:

$$\text{Inflation Gap}_t = \beta \cdot \text{RMB\ Appreciation}_t + \gamma \cdot X_t + \epsilon_t,$$

where $\text{RMB\ Appreciation}_t$ is the month-to-month RMB appreciation against the US Dollar, $\pi_{1,t}$ is the month-to-month relative inflation spread of US households in the bottom income quintile and $\pi_{5,t}$ is that of US households in the top income quintile. Column (1) in Table IA.8 confirms the positive correlation between RMB appreciation and the US inflation gap is statistically significant, with the F-statistic equals to 45.86. In column (2), I control for potentially co-moving variables such as aggregate inflation rates, fed funds rates, gas price changes, and dollar index changes. In column (3), I add month fixed effects to absorb seasonality, and in column (4), I add year as a control variable to capture the linear long-run trend. The positive correlation between RMB appreciation and the inflation gap remains robust among all specifications.

5.1.2 The Exclusion Restriction

The identification assumption is that RMB appreciation against USD affects mortgage borrowing and housing investments through and only through the inflation heterogeneity channel. Although there is no way to test the exclusion restriction perfectly, I try to address it in several steps. First, there are reasonable concerns about whether RMB appreciation can affect household incomes in a heterogeneous way and consequently change their mortgage and housing decisions. If the bottom income households were more likely to work in industries that face strong competition from China, RMB appreciation against USD can potentially affect their incomes to a greater extent. In Section IA.2, I test this alternative hypothesis using geographic variations in trade exposures to China. The effects of relative inflation spreads on mortgage borrowing and housing investments are equally strong in counties both with low and high China trade exposures, which suggests the alternative income channel hypothesis does not drive the results. Second, it is also possible that RMB appreciation affects the US housing market through an interest rate channel. In the influential global saving glut speech, Bernanke (2005) proposes that excessive savings from developing countries, especially China, contribute to the low interest rate environment in US. The appreciation of RMB may affect US interest rates by changing China's foreign reserve and demand for US bonds, which may change US interest rates and affect low income US households and high income US households differently. Third, exchange rate fluctuations can also be the results of US monetary policy shocks. Higher US domestic interest rate can make USD appreciate relative to other foreign currencies. The last two alternative channels can be eliminated by directly controlling short term and long term interest rates and allowing households to have different sensitivities towards the interest rate environment. The results are still robust and significant, both statistically and economically.

5.1.3 Evidence from the Instrumental Variable Approach

After validating the RMB appreciation against USD as an instrumental variable for US inflation heterogeneity across income groups, I run a two-stages OLS regression following the baseline specification 1:

The first and second stage equations in the IV specification are

$$
\begin{aligned}
\ln(Num_{k,j,c,t} + 1) &= \beta \cdot \hat{\pi}_{j,t} + \gamma \cdot X_{k,j,c,t} + \psi_{c,t} + \eta_k + \epsilon_{k,j,c,t}, \\
\pi_{j,t} &= \tilde{\beta}_j \cdot Z_t + \tilde{\alpha},
\end{aligned}
$$

where k indexes census tract, t the year, $Num_{k,j,c,t}$ is the number of mortgages originated for home purchase at census tract k in year t recorded by HMDA. $\pi_{j,t}$, the relative inflation spread of income quintile j in year t, is instrumented by $Z_t = \text{RMB Appreciation}_t$, which is the appreciation of RMB against USD over the past 12 months. $\psi_{c,t}$ are the county by year fixed effects, and η_k are the census tract fixed effects. $X_{k,j,c,t}$ are other control variables of census tract k, including the log of median income, Zillow home value at the census tract, 1-year local housing market return, 5-year housing market return, 1-year local rent growth, and local rent index. I also control for short term and long terms interest rates and national inflation rates and allow heterogeneous sensitivities to those variables across income groups. Under the identification condition $\mathbb{E}[\tilde{\beta}_j \cdot Z_t \cdot \epsilon_{k,j,c,,t} | X_{k,j,c,t}, \psi_{c,t}, \eta_k] = 0$ and relevance condition $\mathbb{E}[\tilde{\beta}_j \cdot Z_t \cdot \pi_{j,t} | X_{k,j,c,t}, \psi_{c,t}, \eta_k] \neq 0$, the coefficient β gives the effect, causally induced by RMB appreciation, of a one percentage point increase in relative inflation spreads on the increase in log one plus the number of mortgages for an average

Table 1: **Mortgage Borrowing and Inflation Heterogeneity: RMB Appreciation as IV**

The second stage equation and the first stage in the IV specifications are

$$\ln(Num_{k,j,c,t} + 1) = \beta \cdot \hat{\pi}_{j,t} + \gamma \cdot X_{k,j,c,t} + \psi_{c,t} + \eta_k + \epsilon_{k,j,c,t},$$
$$\pi_{j,t} = \tilde{\beta}_j \cdot Z_t + \tilde{\alpha},$$

where k indexes census tract, t the year, $Num_{k,j,c,t}$ is the number of mortgages originated for home purchase at census tract k in year t recorded by HMDA. $\pi_{j,t}$, the relative inflation spread of income quintile j in year t, is instrumented by $Z_t = \text{RMB Appreciation}_t$, which is the appreciation of Chinese Yuan relative to US Dollar over the past 12 months. $\psi_{c,t}$ are the county by year fixed effects, and η_k are the census tract fixed effects. $X_{k,j,c,t}$ are other control variables of census tract k, including the log of median income, Zillow home value at the census tract, 1-year local housing market return, five-year housing market return, 1-year local rent growth, and local rent index. I also control for short term and long terms interest rates and national inflation rates and allow heterogeneous sensitivities to those variables across income groups. The sample period is from 2005 to 2019. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	ln(Num + 1)				
$\widehat{\pi_{j,t}}$	0.115**	0.156***	0.150*	0.195***	0.175***
	(0.0486)	(0.0486)	(0.0814)	(0.0463)	(0.0468)
1-Year Housing Ret		0.603***	0.585***	0.438***	0.564***
		(0.0975)	(0.0978)	(0.0762)	(0.114)
5-Year Housing Ret		-0.0105***	-0.0105***	-0.00832***	-0.0115***
		(0.00214)	(0.00215)	(0.00173)	(0.00291)
1-Year Rent Growth					0.0887***
					(0.0291)
Observations	660,015	592,313	592,313	592,313	348,801
R-squared	0.9017	0.9018	0.9039	0.9039	0.9037
Inflation Exposure			Yes	Yes	Yes
Interest Rate Curve Exposure				Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

census tract.

The results are shown in Table 1. In column (4), I find that a one percentage point increase in relative inflation spreads leads to a 0.175 increase in log one plus the number of mortgages. The IV estimations are stronger than the OLS estimations in Section 4.4, which suggests that omitted variables biases or reverse causality attenuates the estimated relationship between inflation heterogeneity and mortgage borrowing. The estimated effect is economically large but still within the range of the literature's estimations. For example Malmendier and Nagel (2016) find a 1 pp increase in (birth cohort based) learning-from-experience inflation leads to a 35 percent increase in household mortgage borrowing.

Table IA.9 shows the effect on home ownership using the same instrumental variable design. I find that a one percentage point increase in relative inflation spreads leads to an increase in the home ownership by nine percentage points. Similar to the findings on mortgage borrowing, the IV estimations are stronger than the OLS estimations in Section 4.5.

5.2 Chinese Yuan Exchange Rate Reform: A Quasi Natural Experiment

To further address other identification concerns, I exploit an unexpected reform of Chinese exchange rate system in 2005, which led to an instant and persistent RMB appreciation against USD. I find the unexpected RMB appreciation is associated with a widened gap in both realized inflation and inflation expectations between the low and high income US households. Moreover, there is no effect on income expectation and employment expectations. Consistent with previous findings, I document that housing investments by the low income households increased after the RMB reform.

5.2.1 RMB Exchange Rate Reform on July 21 2005

From 1997 to 2005, the Chinese government maintained a peg of 8.27 RMB per USD. On 21 July 2005, China lifted the peg and moved to a managed float exchange rate system against a basket of major currencies. RMB immediately appreciated by 2.1% against USD within one day, and further appreciated by nearly 20% against USD by July 2008 (Figure IA.1a). Frankel and Wei (2007) show the market was surprised by the reform. RMB suddenly appreciated against USD in both spot and forward markets. Analysts at Citigroup wrote, "The Chinese authorities had always said that they would make an announcement when no one was expecting it. In this regard, they have chosen well."[x] Given the role of China as one of the largest US trading partners, the following RMB appreciation triggered many worries about high inflation in the US (Online Appendix: IA.3).

5.2.2 Chinese Yuan Reform and the US Realized Inflation Heterogeneity

Based on the same arguments as in Section 5.1, I expect the reform to have a greater impact on relative inflation spreads of lower income US households. Data suggest that the realized non-food inflation spreads of the bottom income US households rose after the Chinese Yuan reform. I use the Nielsen Consumer Panel data to estimate household level realized inflation, focusing on non-food retail products, for example general merchandise and health&beauty care, which are much more likely to be imported from China.

Figure 4a plots the time series of average realized non-food relative inflation spreads for each income quintile. To test whether the widened inflation heterogeneity is statistically significant, I regress the realized month-to-month relative inflation spreads on the interaction of income quintile dummies and a post dummy variable equal one after the RMB reform on July 21 2005.

$$\pi_{i,j,m,t} = \alpha + \beta \cdot Post_t \cdot Qunitile_{i,j} + h_i + \psi_{m,t} + \eta_{j,t} + \epsilon_{i,j,m,t},$$

where i indexes household, j income quintile, m metropolitan area, t the year. To control for macro and local economy variations, I include $\psi_{m,t}$ MSA-year-month fixed effects. As a result, I compare the realized inflation changes of other income groups with the top income quintile within the same metropolitan area. I also control for h_i household fixed effects and $\eta_{j,t}$ income quintile by year fixed effects. The results are presented in Figure 5d, which shows that bottom quintile income households experienced higher realized inflation for their non-food consumption baskets after the RMB reform on July 21 2005. The results are consistent Cravino and Levchenko (2017), where they find lower income Mexican households experienced higher inflation after Mexico's currency devaluation.

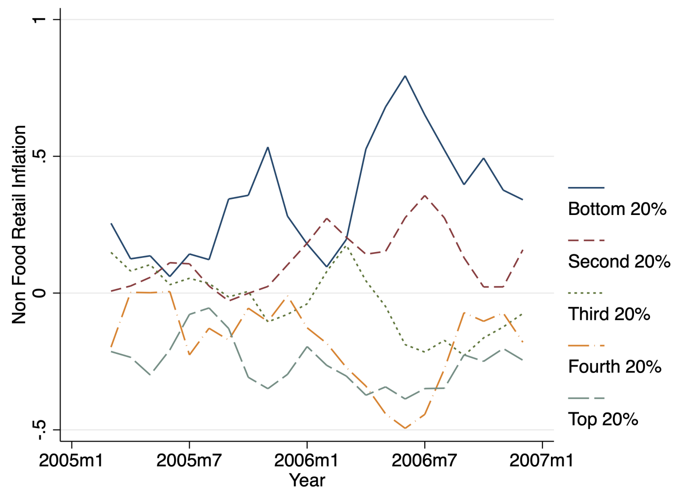
5.2.3 RMB Reform and the US Inflation Expectation Heterogeneity

Consistent with larger realized inflation spreads, I also find that the bottom income US household disproportionally increased their inflation expectation at the same time, us-

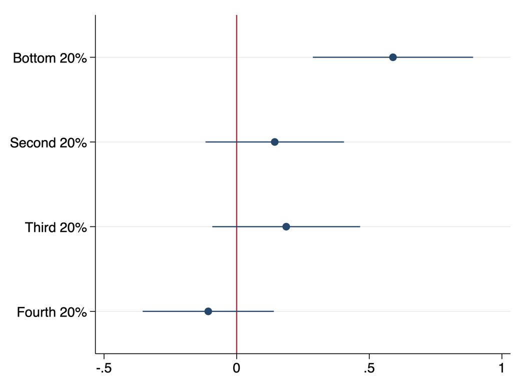
[x] "Washington, Wall Street React To Chinese Yuan Revaluation", Wall Street Journal, July 21 2005.

Figure 4: **Chinese Yuan Exchange Rate Reform and US Realized Inflation Heterogeneity**

Figure 4a plots the average month-to-month relative non-food inflation spreads by income quintiles. Figure 4b shows the widening inflation gap is statistically significant between the botton income quintile and the top income quintile. I regress realized non-food inflation spreads $\pi_{i,t}$ for household i on the interaction of income quintile dummies and a post dummy variable indicating the RMB reform on July 21 2005. MSA-year-month fixed effects, household fixed effects, and income quintile by year fixed effects are included.



(a) Non-Food Goods Relative Inflation Spreads



(b) Difference Relative to the Top 20% Income Qunitile ing disaggregated monthly household interviews on inflation expectation from Michigan Surveys of Consumers from 2003 to 2007.

$$\text{Expectation}_{i,m,t} = \beta \cdot \text{Bottom}_{i,m,t} \cdot \text{Reform}_t + \gamma \cdot X_{i,m,t} + \eta \cdot Z_{i,m,t} + \psi_{m,t} + \epsilon_{i,m,t},$$

where $\text{Expectation}_{i,m,t}$ is the inflation or income or employment expectation of survey participant i in year-month t at region m, the dummy variable $\text{Bottom}_{i,t}$ equals to one if the survey participant belongs to the bottom quintile, and Reform_t is a dummy variable equal to one if t is after July 21 2005. $X_{i,m,t}$ are the participant's demographic characteristics, including income, gender fixed effects, education fixed effects, age fixed effects, and birth year fixed effects to account for potential cohort effects (i.e. Malmendier and Nagel (2016)). Moreover, I also control $Z_{i,m,t}$, which are participants' expectations of future income, unemployment, interest rate, and aggregate economy to make sure other expectations do not drive the result. $\psi_{m,t}$ are the region by year by month fixed effects to absorb any aggregate and local economy variations.

The results are reported in Table IA.10. The bottom income households had both higher 1-year and 5-year forward inflation expectations. However, this is no differences in income expectation, as shown in Columns (5)-(6), nor in other in macro economy expectations such as gas price, unemployment rate, and economy condition, as shown in Table IA.11. The heterogeneity in inflation expectation responses to the RMB reform does not mean or require households to directly learn macro-economy news and update their beliefs accordingly. Instead, households can update their inflation expectation from their daily experience, such as grocery shopping, as shown by DAcunto et al. (2021).

5.2.4 Chinese Yuan Reform and US Housing Transactions

Given the RMB reform happened as a surprise to the market and created heterogeneous impacts on both inflation expectation and realized inflation of US households across income groups, I can use a standard difference in differences approach to estimate its effect on household mortgage borrowing. Bottom income households are regarded as the treated group, as data suggest the associated rise in both realized inflation spreads and inflation expectation spreads were strongest for them.

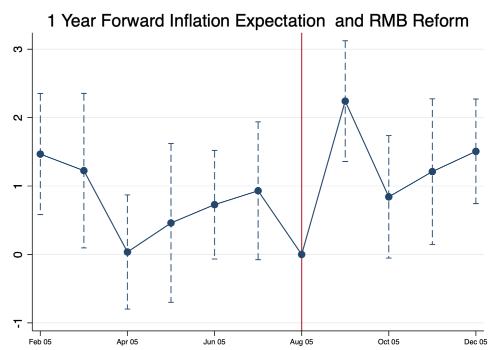
Instead of using annual data from HMDA and ACS, I use high-frequency real estate transaction data from ZTRAX. The relative higher frequency with monthly data can overcome the potential contamination because of the 2008-2009 financial crisis if using annual

Figure 5: **Chinese Yuan Exchange Rate Reform and US Household Expectation**

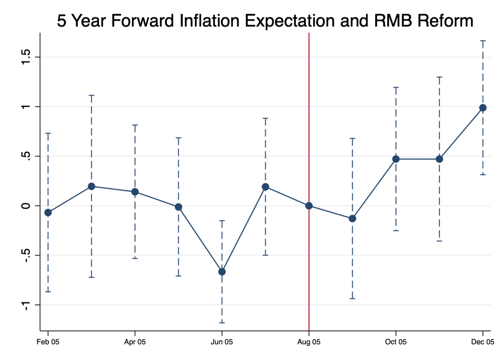
Figures (a)-(d) plot differences in expectations of inflation, income, and unemployment between the bottom income households and other households around the Chinese Yuan reform on July 21 2005. The exact specification is as follows:

$$\text{Expectation}_{i,m,t} = \beta \cdot \text{Bottom}_{i,m,t} \cdot \text{Reform}_t + \gamma \cdot X_{i,m,t} + \eta \cdot Z_{i,m,t} + \psi_{m,t} + \epsilon_{i,m,t},$$

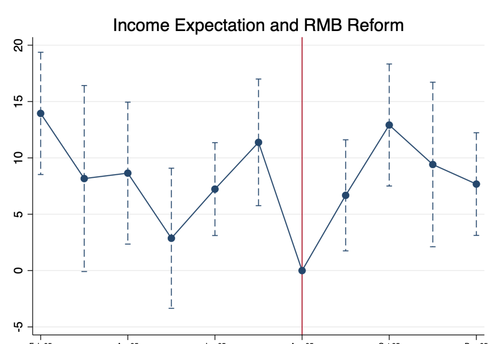
where $\text{Expectation}_{i,m,t}$ is the inflation or income or employment expectation of survey participant i in year-month t at region m. Reform_t is a dummy variable and equals to one if year-month t is after the RMB Reform on July 21 2005. $\text{Bottom}_{i,m,t}$ equals to one if the participant i belongs to the bottom income quintile. $X_{i,m,t}$ are the participant's demographic characteristics, including income, gender fixed effects, education fixed effects, age fixed effects, and birth year fixed effects. $\psi_{i,m,t}$ are the region by year by month fixed effects to absorb any aggregate and local economy variations. Standard errors double clustered at the year-month level and birth year level.



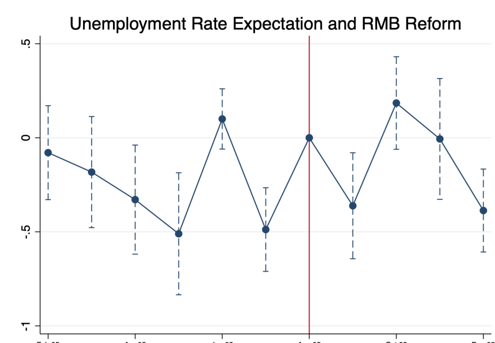
(a) 1 Year Forward Inflation Expectation



(b) 5 Year Forward Inflation Expectation



(c) 1 Year Forward Income Expectation



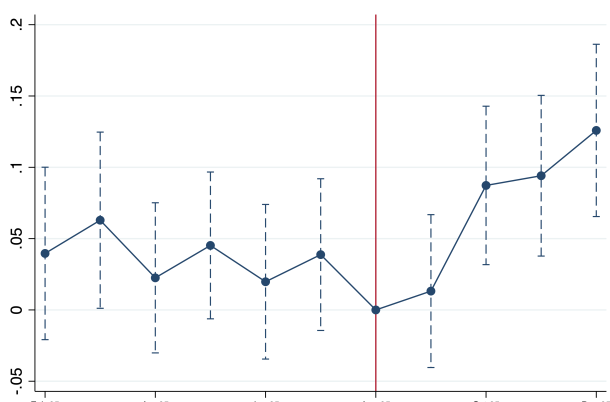
(d) 1 Year Forward Unemployment Expectation

Figure 6: **Housing Transactions around the Chinese Yuan Reform**

This figure shows the estimated coefficients from the following regression at the monthly level.

$$\ln(Num_{z,k,j,t} + 1) = \beta \cdot \text{Bottom}_z \cdot \text{Reform}_t + \gamma \cdot X_{z,k,j,t} + \psi_{k,t} + \eta_{z,t} + \xi_{z,t} + \epsilon_{z,k,j,t}$$

where $Num_{z,k,j,t}$ is the number of mortgages originated at zip code z in year-month t. Bottom_z is a dummy variable and equals one if zip code z belongs to the bottom income quintile. Reform_t is also a dummy variable and equals to one if year-month t is after the RMB Reform in July 2005. $\psi_{k,t}$ are the county by year by month fixed effects, $\eta_{z,t}$ are the zip code by year fixed effects, $\xi_{z,t}$ are the zip code by month fixed effects. $X_{z,k,j,t}$ are other control variables, including last month's home value at the zip code and month-to-month local home value appreciation. With county-by-year-by-month fixed effects, I can tightly control for any county-level time-varying macroeconomic variations. With zip code by year fixed effects, I can control for the long-run variations at a zip code level associated with the housing market boom and bust between 2003 and 2007. The zip code-by-month fixed effects are further used to control for seasonality variations in the zip code level housing markets. The sample period is from 2003 to 2007. Standard errors clustered at the county level and income quintile by year level .



frequency data.

$$\ln(Num_{z,k,j,t}+1) = \beta \cdot \text{Bottom}_z \cdot \text{Reform}_t + \gamma \cdot X_{z,k,j,t} + \psi_{k,t} + \eta_{z,t} + \xi_{z,t} + \epsilon_{z,k,j,t}$$

where $Num_{z,k,j,t}$ is the number of mortgages based housing transaction at zip code z in year-month t. Bottom$_z$ is a dummy variable and equals one if zip code z belongs to the bottom income quintile. Reform$_t$ is also a dummy variable and equals to one if year-month t is after the RMB Reform in July 2005. $\psi_{k,t}$ are the county by year by month fixed effects, $\eta_{z,t}$ are the zip code by year fixed effects, $\xi_{z,t}$ are the zip code by month fixed effects. $X_{z,k,j,t}$ are other control variables, including last month's home value at the zip code and month-to-month local home value appreciation. With county-by-year-by-month fixed effects, I can tightly control for any county-level time-varying macroeconomic variations. With zip code by year fixed effects, I can control for the long-run variations at a zip code level associated with the housing market boom and bust between 2003 and 2007. The zip code-by-month fixed effects are further used to control seasonality variations in the zip code level housing markets. The sample period is from 2003 to 2007, including two years before the RMB reform and two years after.

The results are shown in Table IA.12 and Figure 6. Consistent with all previous findings, after the RMB reform in July 2005, the bottom income households started to increase housing investments compared to the other households in the same county in the same year-month. Given the high frequency nature of this empirical design, the increase in mortgage borrowing can be interpreted as causally driven by the RMB reform and following widened inflation heterogeneity. I also control for the share of private labeled securtization (PLS) mortgages among all mortgages and the share of mortgages with misreported owner occupancy and second lien among all PLS mortgages, at the zip code by year-month level. The results are robust to the additional controls, which suggests the estimation is not driven by the subprime bubble documented by Mian and Sufi (2009) and Griffin and Maturana (2016). To isolate from the effect of Hurricane Katrina in August 2005, I exclude southern states including Mississippi, Louisiana, and Florida from the sample.

6. Model and Counterfactual Analyses

As shown in previous sections, households response to inflation heterogeneity by relocating their portfolios between the "centralized" mortgage market and "segmented" housing markets. In this section, I explore the theoretical implications of the systematic inflation heterogeneity across income groups on asset prices, the cross-sectional housing dispersion, and household welfare in a general equilibrium framework by comparing to a counterfactual world without inflation heterogeneity.

6.1 Environment

Consider an overlapping-generation endowment economy with J ($J = 2$, low and high income) groups of households who live in I ($I = 2$, low and high income) islands with fixed housing supplies. Each group has a continuum of households with a measure of one. Each household lives for three equally long periods (young, middle age, and retirement), and receives a deterministic life stage labor income process with idiosyncratic shocks.

In the economy, there are three financial markets: one "centralized" bond market, one "segmented" housing market in the low income island, and one "segmented" housing market in the high income island. All households can save via the "centralized" bond market with a nominal risk-free interest rate $R_{f,t}$. Meanwhile, only homeowners can borrow by the same nominal interest rate using their houses as collateral but subjective to a maximum loan-to-value ratio η. Uncollateralized borrowing is not allowed. I assume there are two separate housing markets for low income households and high income households, based on the documented increasing geographic income segregation (i.e. Reardon and Bischoff (2011), Guerrieri et al. (2013), and Landvoigt et al. (2015)). To mimic the realistic mixture of households' incomes and their housing locations, the two housing markets are not completely segmented. A small proportion of low income households can live in the high income island, and vice versa. Let $\lambda_{j,i}$ to be the fraction of households in group j lives in island i, with $\sum_{i \in I} \lambda_{j,i} = 1$. In the background, there are competitive financial institutions who hold residential rental capital, as in İmrohoroğlu et al. (2018). The rental rate is determined by the competitive financial institutions such that it covers the interest payments, depreciation, and taxes,

$$r_{i,t} = P_{i,t} \cdot (R_{f,t} + \delta + \tau - 1),$$

where $r_{i,t}$ is the rental price at island i and time t, $P_{i,t}$ is the house price, δ is the depreciation rate δ, and τ is the property tax rate τ.

6.1.1 Household's Problem

At time t, a household in income group j at age n receives nominal labor income $w_{j,t,n} = w_j \cdot \alpha_n \cdot \epsilon_{j,t,n}$, where w_j is the average income for group j, α_n is the life stage labor efficiency to capture a deterministic life cycle income process, and $e_{j,t,n}$ represents the idiosyncratic stochastic shock to labor income every period.[xi]

Households consumes retail goods c and housing service h, and the utility from a bundle of $\{c, h\}$ is[xii]

$$u(c,h) = \frac{\left(c^{\theta} \cdot h^{1-\theta}\right)^{1-\gamma}}{1-\gamma}.$$

Households in group j at age n has a specific basket of retail goods that they would like to consume. The nominal price of such basket is $p_{j,n}$, which follows an exogenous relative inflation spread π_j. To keep the economy stationary, the price of basket for each newly born generation is set to be $p_{j,0} = 1$. The national average inflation is assumed to be zero.

Households maximize expected utility. At the young stage, household j in island i born at time t saves $s_{j,i,t,0}$ via the centralized bond market. In addition, the household chooses a rental house with size $h_{j,i,t,0}$ to live for the young stage. The household also needs to choose to rent or buy a house with size $h_{j,i,t+1,1} = h_{j,i,t+2,2}$ in the local housing market to live for the coming middle age and retirement stages. This assumption is made to reduce the dimension of policy space and features the illiquidity of the housing market. If $h_{j,i,t+1,1}$ is below a threshold h_{min}, the household has to rent the property. If $h_{j,i,t+1,1}$ is above the threshold h_{min}, the household has to buy the property and becomes a homeowner. Conditional on owning the property, the household is allowed to use it as collateral and borrow a mortgage from the centralized bond market with the nominal interest rate of $R_{f,t}$, but subjective to a maximum loan-to-value ratio η.

[xi] I assume that the nominal income growth process is uncorrelated with the relative inflation spread process. This assumption is consistent with the empirically near-zero correlation between group-income-growth-spread and relative inflation spread, as shown in the Online Appendix Section IA.4.

[xii] I assume Cobb-Douglas utility function because household spends a relatively stable share of the nominal budget on housing services, as shown by Davis and Ortalo-Magné (2011) and Favilukis and Van Nieuwerburgh (2021).

So, in the young stage, the household solves

$$\max_{s_{j,i,t,0},\, h_{j,i,t,0},\, h_{j,i,t+1,1}} V_{j,i,t,0} = u(c_{j,i,t,0}, h_{j,i,t,0}) + \beta \cdot \mathbb{E}V_{j,i,t+1,1}(s_{j,i,t,0}, h_{j,i,t+1,1})$$

subject to the budget constraint

$$\begin{aligned} c_{j,i,t,0} + r_{i,t} \cdot h_{j,i,t,0} &= w_{j,i,t,0} - s_{j,i,t,0} - h_{j,i,t+1,1} \cdot P_{i,t} \cdot \mathbb{1}(h_{j,i,t+1,1} \geq h_{min}), \\ 0 &\leq s_{j,i,t,0} + h_{j,i,t+1,1} \cdot P_{i,t} \cdot \eta \cdot \mathbb{1}(h_{j,i,t+1,1} \geq h_{min}), \end{aligned}$$

where $\mathbb{1}(h_{j,i,t+1,1} \geq h_{min})$ is the indicator function for home owners.

At the middle age stage, the household enjoys a housing service flow $h_{j,i,t+1,1}$ based on the rental contract or home purchase contract she signed when young. Based on the nominal savings or borrowings carried from the young stage and her realized labor income, the household chooses her savings or borrowings $s_{j,i,t+1,1}$ for the retirement stage and her retail good consumption, whose price grows by an inflation rate of π_j. The household solves

$$\max_{s_{j,i,t,1}} V_{j,i,t+1,1} = u(c_{j,i,t+1,1}, h_{j,i,t+1,1}) + \beta \cdot \mathbb{E}V_{j,i,t+2,2}(s_{j,i,t+1,1}, h_{j,i,t+1,1})$$

subject to the budget constraints

$$\begin{aligned} & e^{\pi_j} \cdot c_{j,i,t+1,1} + s_{j,i,t+1,1} + h_{j,i,t+1,1} \cdot r_{i,t+1} \cdot \mathbb{1}(h_{j,i,t+1,1} < h_{min}) \\ & \qquad = w_{j,i,t+1,1} + s_{j,i,t,0} \cdot R_{f,t} - h_{j,i,t+1,1} \cdot P_{i,t+1} \cdot (\tau + \delta) \cdot \mathbb{1}(h_{j,i,t+1,1} \geq h_{min}), \\ & \quad 0 \leq s_{j,i,t+1,1} + h_{j,i,t+1,1} \cdot P_{i,t+1} \cdot \eta \cdot \mathbb{1}(h_{j,i,t+1,1} \geq h_{min}), \end{aligned}$$

where $h_{j,i,t+1,1} \cdot P_{i,t+1} \cdot (\tau + \delta)$ captures the cost of house depreciation and property tax as a home owner.

At the retirement stage, the household does not make any active decisions. The household still enjoys the housing service flow $h_{j,i,t+1,1}$ based on the rental contract or home purchase contract she signed when young. At the same time, the household spends on retail good consumption, whose price grows by an inflation rate of π_j, financed by her realized labor income and all savings carried from the middle age stage including the home value.

$$V_{j,i,t+2,2} = u(c_{j,i,t+2,2}, h_{j,i,t+2,2})$$

subject to the budget constraints

$$
\begin{aligned}
e^{2\cdot\pi_j} \cdot c_{j,i,t+2,2} + h_{j,i,t+2,2} \cdot r_{i,t+2} \cdot \mathbb{1}(h_{j,i,t+2,2} < h_{min}) \\
= w_{j,i,t+2,2} + s_{j,i,t+1,1} \cdot R_{f,t+1} + h_{j,i,t+2,2} \cdot P_{i,t+2} \cdot (1-\tau+\delta) \cdot \mathbb{1}(h_{j,i,t+2,2} \geq h_{min}), \\
h_{j,i,t+2,2} = h_{j,i,t+1,1},
\end{aligned}
$$

6.1.2 General Equilibrium

In equilibrium, given the prices $\{P_{i,t}, R_{f,t}\}$ and the distribution of idiosyncratic i.i.d. income shock $\epsilon_{j,i,t,n}$, households in group j on island i solve their problems by choosing quantities $\{h_{j,i,t,0}, h_{j,i,t,1}, s_{j,i,t,0}, s_{j,i,t,1}\}$.

House price $P_{i,t}$ adjusts to clear the housing market in island i with fixed supplies:

$$
\sum_j \left[\lambda_{j,i} \cdot \left(\int_\epsilon h_{j,i,t,0}(\epsilon) + \int_\epsilon h_{j,i,t,1}(\epsilon) + \int_\epsilon h_{j,i,t,2}(\epsilon)\right)\right] = H_i
$$

The national risk free rate adjusts to clear the centralized bond (mortgage) market with the net supply of 0:

$$
\sum_i \sum_j \left[\lambda_{j,i} \cdot \left(\int_\epsilon s_{j,i,t,1}(\epsilon) + \int_\epsilon s_{j,i,t,2}(\epsilon)\right)\right] = 0
$$

6.2 Calibration and Numerical Results

For tractability, I assume the number of income groups $J = 2$ and the number of islands $I = 2$. There are a high income group and low income group in the economy, as well as a high income island and a low income island. Households live through three life stages (young, middle age, retirement). They work during the first two life stages, representing ages 21–60, and are retired in the last life stage representing ages 60–80. Each time period is selected to be 20 years.

Table 2 summarizes the parameters used in the baseline calibration. Following İmrohoroğlu et al. (2018), I assume 1) the subjective time discount factor, β, to be 0.96, 2) the relative risk aversion, γ, is 5, 3) relative weight of housing in the utility function, θ, to be 0.33, 3) a maximum loan-to-value (LTV), η, at 80 percent, 4) a property tax rate, τ, at 1 percent, 5) a housing depreciation rate, δ, at 2 percent, 6) the life stage working efficiency, α_n, to be 0.75 for the young period, 1.31, for the middle age, and 0.4 for the retirement age, and

Table 2: Calibration of the Baseline Scenario

	High Income	Low Income	Source	
			Literature	Data
Number of groups J:	2		✓	
Coefficient of relative risk aversion γ:	5		✓	
Discount factor β:	0.96		✓	
Housing share in utility θ_j:	0.34			✓
Relative Inflation Spread π_j:	-0.3pp	0.3pp		✓
Endowment w_j:	60,000	30,000		✓
Population distribution $\lambda_{j,-j}$:	0.2			✓
Life-stage efficiency profile:	0.75, 1.31, 0.4		✓	
Idiosyncratic income volatility σ^2:	0.01		✓	
Housing depreciation rate δ:	0.02		✓	
Property tax rate τ:	0.01		✓	
Maximum loan-to-value η:	0.8		✓	

7) idiosyncratic income volatility $\sigma_\epsilon^2 = 0.01$. The total supplies of housing are 1 in both islands, with the average house size to be 0.33. The minimal owner-occupied house size $h_{min} = 0.3$, which is around 90% of the average house size, as in İmrohoroğlu et al. (2018). The average annual incomes are calibrated to match the median annual income of the top 50% and bottom 50% income US households respectively. The share of low income households who live in the high income island is estimated based on the 2005 IRS tax return data. I set $\lambda_{j,-j} = 0.2$, which implies 80% of low income households live in the low income island and 20% of them live in the high income island, and the distribution is symmetric for high income households.

To solve the model, I first numerically search the optimal savings decision for middle age households of group i in time t, given their state variables including nominal savings $s_{j,i,t+1,1}$, housing $h_{j,i,t+1,1}$, income shocks $\epsilon_{j,i,t+1,1}$, house price $P_{i,t+1}$, and national interest rate $R_{f,t+1}$. Then I use backward induction to solve the optimal savings $s_{j,i,t,0}$ and housing decisions $h_{j,i,t,0}$ for the young households, given state variables including income shocks $\epsilon_{j,i,t,0}$, house price $P_{i,t}$, and national interest rate $R_{f,t}$. Last, I numerically search in the price space $\{P_{j,t}, R_{f,t}\}$ until both the housing markets and the centralized bond market are cleared.

The model is able to generate comparable moments as what are estimated from the data. First, in data, the fraction of home owners from American Community Survey is 82% for high income households and 53% for low income households. The model delivers very similar numbers, which are 79% and 49% respectively.[xiii] Second, the average home value to income ratio from American Community Survey is 3.0 for high income households and 8.0 for low income households, which are 4.3 and 7.0 in the model. Third, the average house size as the percentages of the national average house size from American Housing Survey is 129% for high income households and 79% for low income households, which are 121% and 80% in the model. Last, the real interest rate during the sample period of 2005 and 2019 is 2.68 pps, measured as the real 30-Year fixed rate mortgage average in the United States. The equilibrium interest rate in the model is 2.23 pps.

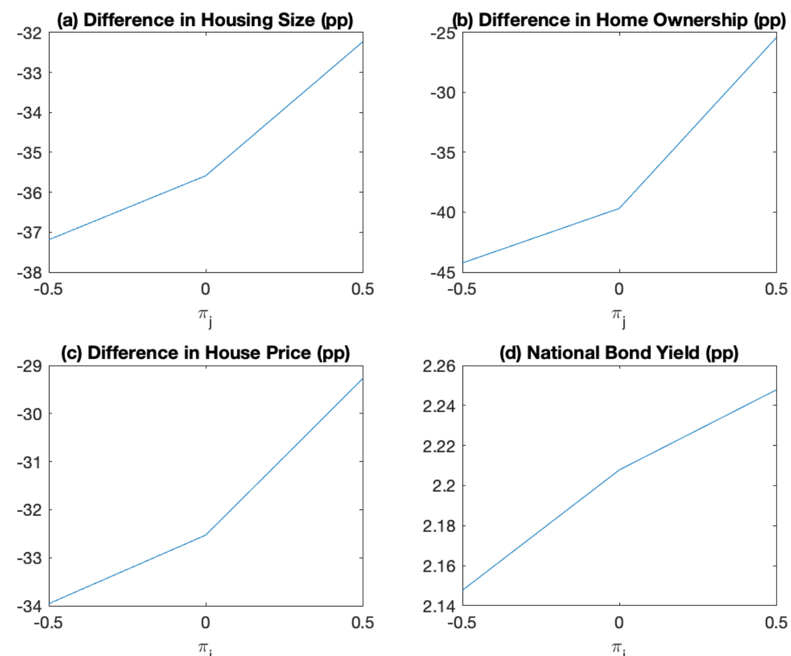
Table 3: **Moments from the Data and the Model**

This table compares moments estimated from the data and moments generated by the model. The fraction of home owners and home value to income ratio are estimated using American Community Survey for both the low income group and high income group. The relative home size as percentages of the national average house size is estimated from US Census Bureau, American Housing Survey 2013. The average real interest rate is the difference between the nominal 30-Year fixed average mortgage rate in the United States from Freddie Mac and the consumer prices inflation, from 2005 to 2019. The response in mortgage & housing, rent, and house price to a 1 percentage point increase in relative inflation spreads π_j is from the instrumental variable estimations.

	Data	Model
Home Ownership (High Income)	82%	79%
Home Ownership (Low Income)	53%	49%
Home Value to Income Ratio (High Income)	3.0	4.3
Home Value to Income Ratio (Low Income)	8.0	7.0
Home Size (High Income)	129%	121%
Home Size (Low Income)	79%	80%
Real Interest Rate	2.68%	2.23%
Response in Mortgage & Housing per 1pp Increase in π_j		
Home Ownership	9.1	9.3
Response in Prices per 1pp Increase in π_j		
Rent	12.2	4.0
House Price	6.6	

Figure 7: **Heterogeneous Inflation and Household Portfolios**

The figures present the steady states for economies with different inflation heterogeneity scenarios. Figures (a) and (b) plot the differences in housing size choices and home ownership choices of low income households compared to high income households. Figure (c) shows the differences in house prices between the low income island and the high income island. Figure (d) shows the national equilibrium interest rate. The x-axes of all subplots are relative inflation spreads of low income households (thus -1 $\times$ relative inflation spreads of high income households), in percentage points between -0.5pp and 0.5pp. The y-axes are also in percentage points.



6.3 Comparative Statics

The general equilibrium model allows me to study counter-factual scenarios, comparing the baseline calibration to a world with no inflation heterogeneity across income groups. Figure 7 shows how the equilibrium household housing decisions and asset prices change with the inflation heterogeneity. Consistent with the empirical findings, households increases their investments in the "local" housing assets, and home ownership consequently. Intuitively, when relative inflation spreads increases, the real values of income and savings in the future periods decrease. With the elasticity of intertemporal substitution $\frac{1}{\gamma} < 1$, the household would like to save more in nominal terms to smooth real consumption in future periods. But the real return from the "centralized" bond market decreases because of high relative inflation spreads. The household will move her savings towards "segmented" housing assets, whose real returns are not directly affected by inflation heterogeneity.

Notably, the instrumental variable estimations show that the low income household increases home ownership by 9 percent in response to a 1pp increase in the relative inflation spread. Households in the model show a sensitivity of 9.3 percent, which is covered by the empirically estimated range.

6.4 Inflation Heterogeneity and Asset Prices

The model suggests inflation heterogeneity across income groups affect not only "segment" house prices and rent but also national interest rates. First of all, when the relative inflation spread π_j rises, Figure 7 (c) shows that the "segment" house price and rent increases, as households prefer to invest more in the "segmented" housing market, where the housing supply is inelastic. Consistent with the model's prediction, table 4 further demonstrates that higher relative inflation spreads indeed lead to higher rent and house prices. Using the ACS data and the same empirical design as in Section 5.1, I find that the rent (house prices) increases by 12 percent (7 percent) in response to a 1pp increase in the relative inflation spread. For comparison, the model predicts an increase by 4 percent.

Furthermore, Figure 7 (d) suggests the national interest rate is higher in the scenario with inflation heterogeneity across income groups, compared to a counterfactual scenario without inflation heterogeneity. If the relative inflation spread of the lower income house-

[xiii] In the simulated economy, I classify all households who consume a house size larger than the minimal owner house size as a home owner, regardless of their age.

Table 4: **Inflation Heterogeneity and Rent and House Prices**

$$\text{Price}_{i,j,k,t} = \beta \cdot \pi_{j,t} + \gamma \cdot X_{i,j,k,t} + \psi_{k,t} + \eta_k + \epsilon_{i,j,k,t}$$

where $\text{Price}_{i,j,k,t}$ is the monthly rent or home value that household i reports. $\pi_{j,t}$ is the relative inflation spread of the income quintile j that household i belongs to in year t. $\psi_{k,t}$ are the county by year fixed effects, and η_k are the public use micro area (PUMA) fixed effects.$X_{i,j,k,t}$ are other control variables, including the log of household income, PUMA home value index, 1 year PUMA home value appreciation, 1 year PUMA rent growth, and PUMA rent index. I also control interest rate term structure and national inflation rate and allow heterogeneous exposure to those variables across income groups. Columns (1) and (2) report the results from OLS, and columns (3) and (4) report the results from the 2SLS using RMB appreciation against US dollar as the instrument. The sample period is from 2005 to 2019. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
	Rent	Home Value	Rent	Home Value
$\pi_{j,t}$	0.0439***	0.0285*	0.122***	0.0661*
	(0.0118)	(0.0157)	(0.0257)	(0.0391)
1-Year Housing Ret	-0.00424	0.102***	-0.00369	0.102***
	(0.00482)	(0.0155)	(0.00484)	(0.0154)
1-Year Rent Growth	0.0392**	-0.0717***	0.0389**	-0.0716***
	(0.0166)	(0.0161)	(0.0169)	(0.0160)
Observations	2,722,445	5,995,590	2,722,445	5,995,590
R-squared	0.446	0.456	0.446	0.456
Inflation Exposure	Yes	Yes	Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

holds rises by 1pp from -0.5pp to 0.5pp, the national equilibrium interest rate will increase from 2.15pp to 2.25pp, by 5 percent. The resulted higher interest rate can be explained by the sharp increase in mortgage borrowing demand from lower income households who choose to become home owners because of higher relative inflation spreads.

6.5 Inflation Heterogeneity and the Cross-sectional Home Ownership

The model can also offer an estimation of how much of the cross-sectional home ownership dispersion can be contributed to or attenuated by the inflation heterogeneity across income groups, under the model's assumptions.

The model suggests that the cross-sectional difference in home ownership by income groups is reduced by 33% compared to the difference in data, as higher relative inflation spreads encourage low income households to hold more real estate. Meanwhile, the cross-sectional difference in owner-occupied house size by income groups is reduced by 49 percent compared to the difference in data, as low income households tend to buy bigger houses as well. Table 5 shows the average home ownership, owner-occupied house size, and renter-occupied house size by income groups under two scenarios with and without inflation heterogeneity across income. The reported house size is in the percentages of the average house size in the economy.

However, the model also suggests the increase in home ownership creates a thicker left tail distribution of housing consumption within the low income households. Renters with the bottom realized labor income are constrained by the minimal owner house size. Even if they want to, they can not afford the down payment, purchase a house and, save for future consumption. In fact, their housing consumption is crowed out by higher house price, given housing supply is inelastic. The 5th percentile of house size consumed within the low income group drops by 9.3 percent from 54% of the average house size to 50% of the average house size.

Figure 8 further demonstrates the increase in home ownership and the crowding out within the low income group when relative inflation spreads rise, by plotting the distributions of house size choices for low income households in low income island, low income households in high income island, high income households in low income island, high income households in high income island. Figures (a) and (b) plot the scenarios with and without inflation heterogeneity across income distribution respectively. The red line indicates the minimal size of owner occupied house. Compared to the no inflation heterogeneity counterfactual world, the share of home owners increases for both low income households living in low income island and low income households living in high income island. At the same time, however, the fractions of low income renters living in a smaller house increase in both islands. Consistent with this crowding out within the group, the standard deviation of house size distribution for low income households increases from 16% to 21%.

Empirical results also support the model's predictions, as shown in Table IA.13. I find that, within an income group, the effects of relative inflation spreads on home ownership are much weaker for relatively lower income and young households. Within a group, relatively lower income and young households are more likely to be renters and can not afford the down payment of buying a house. In fact, a rise in relative inflation spreads reduces the home ownership of young and relatively lower income households within the group.

Table 5: **Inflation Heterogeneity and Cross-sectional Housing Consumption**

This table shows the average home ownership, owner-occupied house size, and renter-occupied house size by income groups under two scenarios with and without inflation heterogeneity across income. House size is in the percentages of the average house size in the economy.

	Data		Model: Inflation Heterogeneity Scenario			
			Yes		No	
Income Group	Low	High	Low	High	Low	High
Home Ownership (%)	53	82	49	78	38	78
Owner House Size (%)	107	142	113	133	99	136
Renter House Size (%)	60	75	60	68	66	63
SD of House Size (Within, %)			21	28	16	28
5th Percentile House Size (Within, %)			50	77	54	79

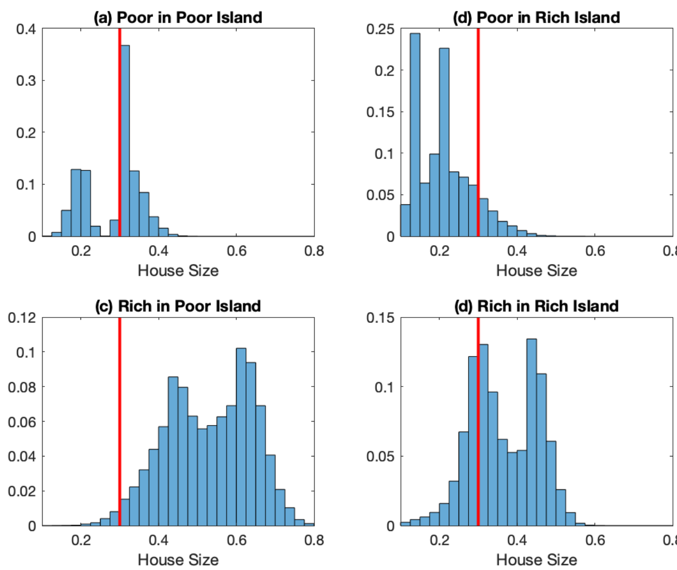
6.6 The Cross-sectional Dispersion in Welfare

Meanwhile, despite reducing the cross-sectional dispersion in home ownership, inflation heterogeneity increases the dispersion in welfare across income groups. Although being

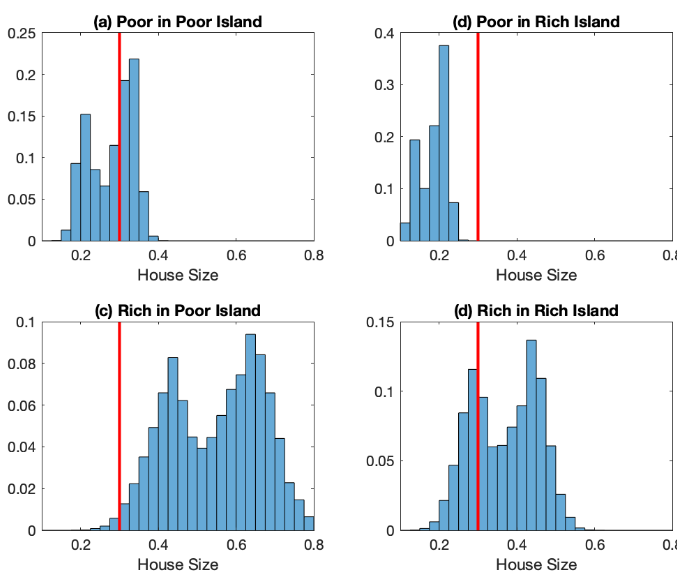
Figure 8: **House Size Choices**

The figures present the distributions of house size choices for low income households in the low income island, low income households in the high income island, high income households in the low income island, high income households in the high income island. Figures (a) and (b) plot the scenarios with and without inflation heterogeneity across income distribution respectively. The red line indicates the minimal size of owner occupied house.

(a) With Inflation Heterogeneity



(b) Without Inflation Heterogeneity



able to mitigate higher relative inflation spreads by using housing assets, welfare calculation suggests households in the low income group unconditionally are worse off. First of all, low income households experience a drop in real labor income as a result of inflation heterogeneity. Second, even if owning a house, the nominal market value of rent and house prices adjust less than one to one to relative inflation, which means a lower real return of savings, also as a result of inflation heterogeneity.

Table 6 compares households under two inflation heterogeneity scenarios. In the first scenario, relative inflation spreads are zero for both high income households and low income households. In the second scenario, the relative inflation spread is 0.3pp for low income groups and -0.3pp for high income households. I classify households into eight types based on their income groups and home ownership choices under the two inflation heterogeneity scenarios. In the simulated economy, there are 50% of high income households and 50% of low income households. Out of the the 50% low income households, 28.6% are always home owners in both scenarios, 11.3% switch from renters to owners when relative inflation spreads rise, 10.1% of them remain renters, and none of them switch from renters to owners, which features their desire to invest into housing assets. All of the three types of low income households have lower expected utility in the scenario with inflation heterogeneity than in the scenario without inflation heterogeneity. Quantitatively, low income households are worse off by the magnitude as if their consumption were reduced by 5%. Notably, the differences in equivalent consumption changes reported in Table 6 shall not be interprated as the differences caused only by home ownership status. The three types of households are intrinsically not directly comparable, as they have different realized labor income, levels of wealth, portfolios of savings. Moreover, as shown in Table IA.14 with more details, they also tend to live in different locations (i.e. islands in the model), where housing prices are different.

7. Conclusion

When group-specific inflation rises (relative to the national average), I find households increase borrowing from the "centralized" and "standardized" mortgage market and holdings of "real" and "segmented" housing assets. The same pattern holds if I use the Chinese Yuan to US Dollar exchange rate as exogenous shocks to relative inflation spreads for US households across income groups, leveraging that low-income households consume

Table 6: **Welfare Analysis by Household Types**

This table shows the distribution of households based on their home ownership status under two inflation heterogeneity scenarios. In the first scenario, relative inflation spreads are zero for both high income households and low income households. In the second scenario, the relative inflation spread is 0.3pp for low income groups and -0.3pp for high income households. Numbers reported are fourth column are percentages of each type of households in the economy. Column 5 describes the equivalent consumption changes for each group if the economy moves from the first scenario without inflation heterogeneity to the second scenario with inflation heterogeneity.

	Home Owner Status in Inflation Heterogeneity Scenarios			
Income Group	No	Yes	% in Population	Equivalent Consumption Changes
High	Owner	Owner	43.6	5.5%
	Owner	Renter	4.5	6.0%
	Renter	Owner	0	-
	Renter	Renter	1.9	5.8%
Low	Owner	Owner	28.6	-5.9%
	Owner	Renter	0	-
	Renter	Owner	11.3	-4.7%
	Renter	Renter	10.1	-4.4%

more tradable goods in their baskets. The increase in mortgage borrowing and housing investment can be explained by that households relocate their savings to markets where real returns are protected from relative inflation. A calibrated general equilibrium model suggests a smaller dispersion in home ownership between income groups but a greater dispersion in welfare, as a result of inflation heterogeneity.

As shown in this paper, inflation heterogeneity can generate comprehensive impacts on household financial decisions. The systematic heterogeneity in household inflation processes exists not only across income groups but also in other dimensions. Most notably, the geographic inflation heterogeneity across metropolitan areas is an even more salient phenomenon. Figure IA.9 shows the accumulated inflation in San Francisco increased by 67 percent, which in Detroit is only 40 percent. Future studies can explore the geographic inflation heterogeneity and its interaction with the financial markets.

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Internet Appendix for
"Inflation Heterogeneity and Household Financial Decisions Evidence from Housing Markets"

Zhao Zhang

IA.1. Income Growth Spreads and Inflation Spreads

It is important to understand the correlation between inflation heterogeneity and nominal income growth heterogeneity. If the correlation is positive and close to one, inflation heterogeneity does not affect real income growth heterogeneity. If the correlation is small or close to zero, inflation heterogeneity also means heterogeneity in real income growth rates.

Figure IA.10 suggests a small and negative correlation between relative nominal income growth spreads and relative inflation spreads, which means inflation heterogeneity is not offset by nominal income growth heterogeneity. To estimate annual relative spreads of nominal income growth for a given income quintile (compared to the national average), I use the Annual Social and Economic Supplement (ASES) of the Current Population Survey. ASES tracts the same households across two years, which allows me to first estimated the nominal income growth rate for a household and take the average for households within same the income quintile. To remove outliers, the sample is restricted between the 1th and 99th percentiles. Then I calculate the relative spreads of nominal income growth as the deviation from the national average nominal income growth in the same year.

IA.2. Income or Inflation? A Trade Exposure Channel

The exclusion restriction for instruments could be violated if RMB appreciation affects not only inflation heterogeneity but also income heterogeneity between lower income households and higher income households. If lower income households are more likely to work in industries with higher China trade exposure, such as manufacturing industries, RMB appreciation can potentially hurt the competitiveness of Chinese factories and benefit US firms as well as lower income households by improving their employment opportunities and incomes. The improved economic status can encourage home buying and mortgage borrowing, which may potentially explain the documented empirically in the previous sections.

Although the above hypothesis sounds plausible, many will disagree. Notably, Alan Greenspan, the then chairman of the US Federal Reserve, said "U.S. workers would not benefit from reduced Chinese competitiveness" and "Goods that were suddenly to become too expensive to import from China would then be imported from Malaysia, Indonesia, Bangladesh or whoever is the next cheapest maker. South Carolina would definitely not be the next cheaper supplier of textiles..." [xiv]

One way to test this trade-income channel hypothesis is to check whether the effect of relative inflation spreads on mortgage borrowing is particularly stronger in counties with greater China trade exposure. Following David et al. (2013) and their shared data from the authors' website, I construct a measure of county level employment exposure to China based on county level employment compositions by industry as well as each industry's exposure to Chinese competitions. Suppose RMB appreciation affects mortgage borrowing through the income channel. In that case, the effect should be stronger in counties with larger China trade exposures because their employment opportunities might be improved the most once local industries regain competitiveness thanks to the RMB appreciation and higher cost of importing from China. In the following test, I run the 2SLS IV regressions on the subsample with low China trade exposure counties and the subsample with high China trade exposure counties.

Overall, the results do not support the hypothesis that RMB appreciation affects US household mortgage borrowings through a trade-exposure-income channel. The results on mortgage borrowing with HMDA data are reported in Table IA.15. Table IA.16 shows the results on home ownership using ACS data. Consistent across various specification,

[xiv] "Greenspan's Yuan Policy", the Wall Street Journal, May 23, 2005

the effects of relative inflation spreads on mortgage borrowing and home ownership are statistically significant in both low trade exposure and high trade exposure areas. If anything, the effect of the inflation heterogeneity seems to be slightly stronger in low China trade exposure counties, which is the opposite direction of the income hypothesis.

IA.3. Chinese Yuan Reform and the US Inflation

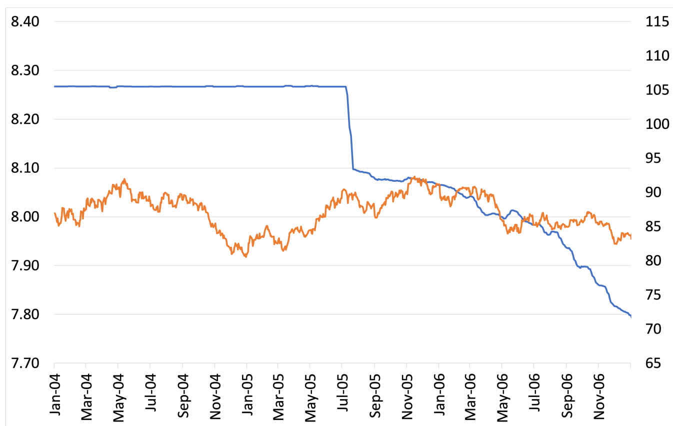
Right after the RMB reform on July 21 2005, many practitioners in Wall Street believed RMB would continue to appreciate. Jay Bryson, global economist for Wachovia Securities, "Will the yuan be 30 percent stronger vs. the dollar a year from now? I doubt that. Could it be 10 percent stronger? Yeah, that's reasonable."[xv]

How would the 2005 Chinese Yuan reform and the expectation of following RMB appreciation affect the inflation in the US? Allen Greenspan, the then Chairman of Fed, expressed his concern about potential domestic inflation risk because of RMB appreciation. Mr. Greenspan said "revaluation would amount to higher prices for consumers, as retailers passed the higher costs of Chines imports by raising prices" and "The effect will be a rise in domestic prices in the United States and, as a consequence of that, we will have other impacts."[xvi] Mr. Greenspan's view on RMB appreciation and US inflation is consistent with the evidence from the 5 year break even inflation expectation (Figure IA.2a) and the price index of imported goods from China (Figure IA.2b). Figure IA.2a shows US inflation expectation rises by about 7 basis points within a three-day window, around the RMB reform on July 21 2005. Figure IA.2b shows price indexes of imports from China start to increase after 2005 while are previously decreasing before 2005. The response of US import price indexes to RMB appreciation is in line with the findings by Amiti and Davis (2009); Auer (2015); Fair (2010); Chen et al. (2011); Bai and Stumpner (2019); Hottman and Monarch (2020).

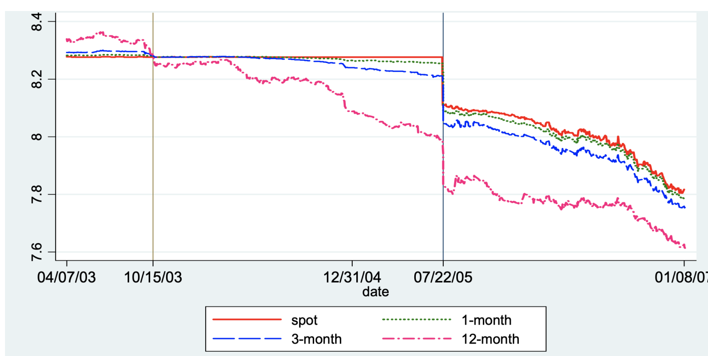
[xv] "China Revalues Yuan", CNN, July 21, 2005.
[xvi] "Greenspan's Yuan Policy", Wall Street Journal, May 23, 2005.

Figure IA.1: **US Dollar to Chinese Yuan Exchange Rate Around July 21 2005**

The blue line in figure (a) shows the daily exchange rate between US Dollar and the Chinese Yuan (RMB) between 2004 and 2006. Before July 21 2005, RMB was pegged to USD with 8.27 RMB per USD. On 21 July 2005, China lifted the peg and moved to a managed float exchange rate system against a basket of major currencies. RMB immediately appreciated by 2.1% against USD within one day. The orange line in figure (a) reports the daily Dollar Index. Figure (b) is from Frankel and Wei (2007) and shows the spot and forward rates of USD/RMB around July 21 2005.



(a) RMB Reform on July 21 2005 (2004 to 2006)

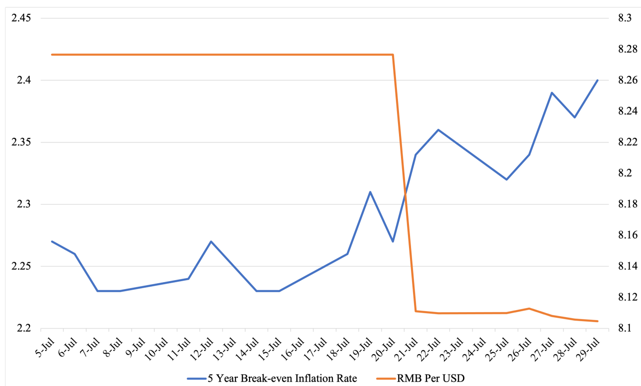


(b) Spot and Forward Rates of USD/RMB

Source: Frankel and Wei (2007)

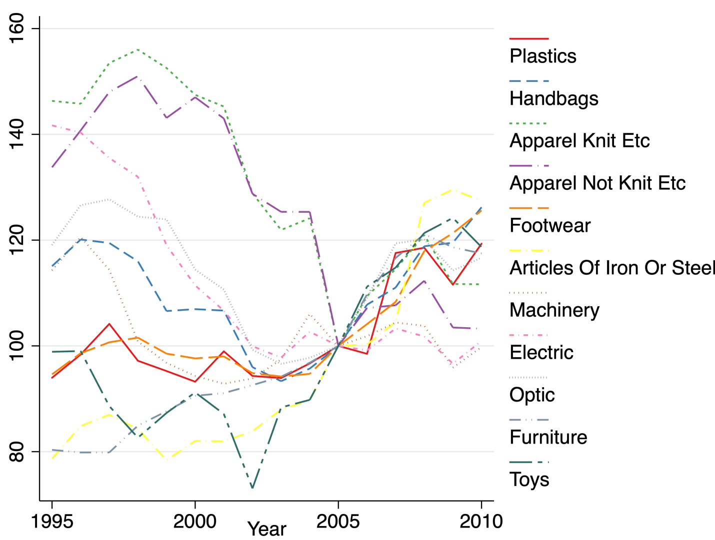
Figure IA.2: **Chinese Yuan Exchange Rate Reform and US Inflation**

Figure IA.2a shows the daily RMB to USD exchange rate and 5-year break even inflation expectation in July 2005. Around the RMB reform on July 21 2005, US inflation expectation rises by about 7 basis points within a three-day window. Figure IA.2b shows the price indexes of the top 10 product categories of US imports from China, based on disaggregated data from U.S. Import and Export Merchandise Trade Statistics following the methodology in Amiti and Davis (2009). The disaggregated US import data use a ten-digit classification of the Harmonized System and covers 12,499 product codes for goods imported from China, with monthly records of total value and unit price of each product code. The top 10 categories constitute about 80 percent of US total imports from China.



(a) RMB Reform on July 21 2005 (2004 to 2006)

Source: Federal Reserve Bank of St. Louis



(b) Import Price Indexes

Source: U.S. Import and Export Merchandise Trade Statistics and Amiti and Davis (2009)

IA.4. First Lien Mortgage or Home Equity Loan?

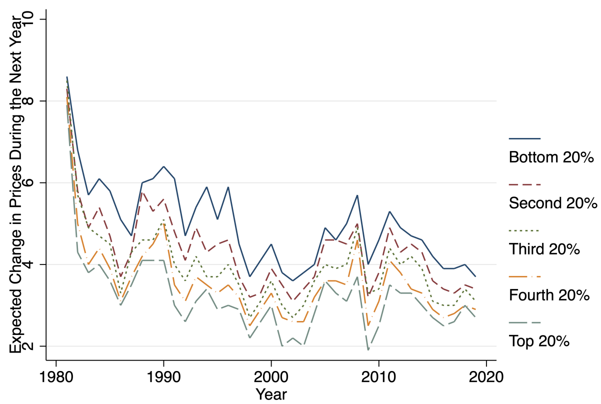
Besides home ownership, ACS asks households whether they have a first lien mortgage and whether they additionally have a home equity loan. Testing the response of mortgage borrowing on inflation heterogeneity by lien types can further disentangle omitted contaminating factors that drive the overall mortgage and housing market. The model in Section 3.2 predicts that household j will decrease savings in the national bond market to finance the investment in the housing market when relative inflation spreads rise. The prediction is consistent with taking a first lien mortgage to buy a house. However, the effect on a second lien loan or home equity loan is ambiguous. Because home equity loans not only can be used to buy real estate properties as first lien loans but also can be used to finance contemporaneous retail goods consumption (Abdallah and Lastrapes (2012)), which means saving less, or to pay off standing debt (Di Maggio et al. (2017)), which means save more in the bond market. While as the model suggests, households will increase nominal savings via the housing market in total but borrow from the bond market when relative inflation spreads rise.

Consistent with the model, Table IA.17 shows that relative inflation spreads π_j are positively correlated with first-lien mortgage borrowing but negatively correlated with the second lien mortgage borrowing. A one percentage point increase in relative inflation spreads is associated with a four percentage points increase in having a first lien mortgage. The same pattern holds using the subsample starting from 2010.

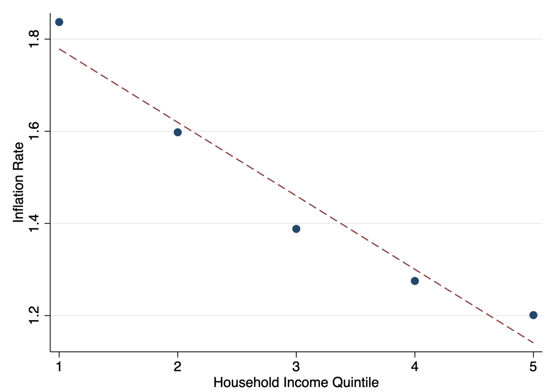
IA.5. Supplement Figures and Tables

Figure IA.3: **Inflation Heterogeneity and Inflation Expectation Heterogeneity**

Figure (a) reports the smoothed monthly average one year forward inflation expectation by household income groups based on Michigan Surveys of Consumers. Figure (b) replicates the main finding from Jaravel (2019) and figure reports the average annual inflation rate across income groups using the Nielsen Consumer Panel data between 2005 and 2015.



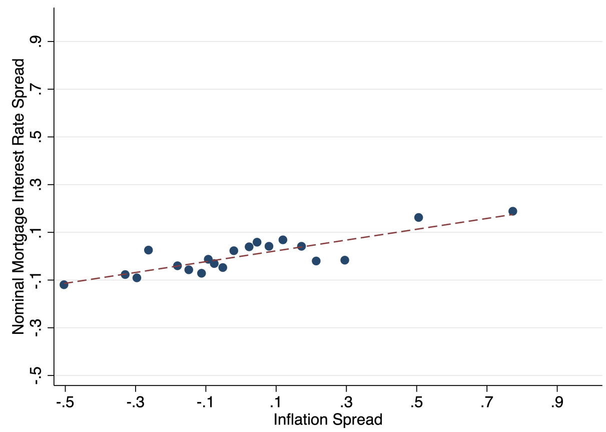
(a) Inflation Expectation Heterogeneity



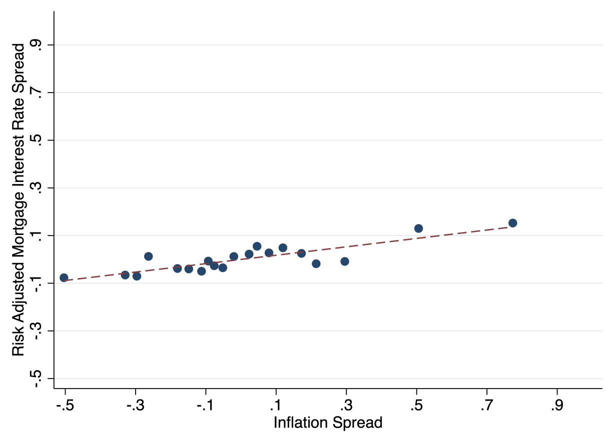
(b) Realized Inflation Heterogeneity

Figure IA.4: **Inflation Heterogeneity and Mortgage Interest Rate Heterogeneity**

Figure (a) reports the correlation between relative inflation spreads and relative nominal mortgage interest rate spreads for each income quintile, using GSE conforming loan performance data. Both spreads are relative to the national average at the same year. Figure (b) reports the default risk adjusted nominal mortgage interest rate across income groups, using GSE conforming loan performance data. Default risks are predicted following Hurst et al. (2016).



(b) Nominal Mortgage Rate (Conforming Loans)



(b) Risk Adjusted Nominal Mortgage Rate (Conforming Loans)

Figure IA.5: **The Distribution of Buyers' Income Quintile and Locations' Income Quintile**

This figure shows the percentage of mortgages borrowed by a household in income quintile i (left axis) to buy a property in a census tract that belongs to income quintile j (right axis), using mortgage level HMDA data between 2005 and 2017.

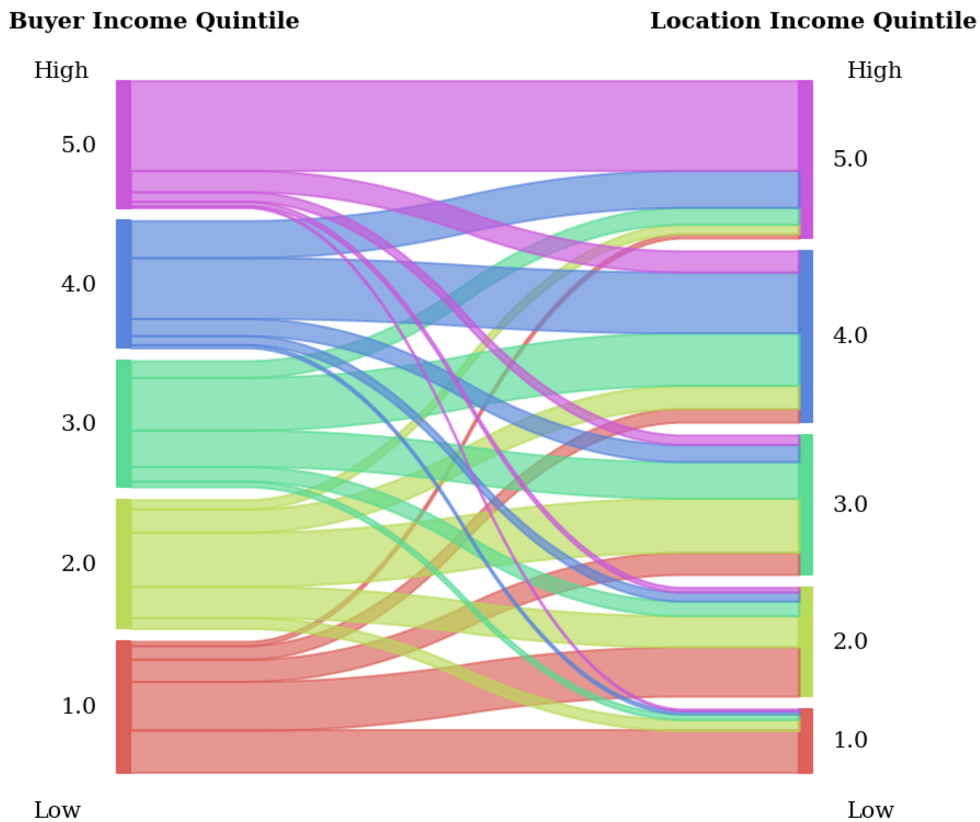


Figure IA.6: **Household Portfolio by Income Quintiles**

Figure IA.6 shows the percentages of each asset category in household balance sheets across income groups. Positive percentages represent net asset positions and negative percentages represent net liability positions. Percentages are calculated based on household net wealth. Data are from Survey of Consumer Finances.

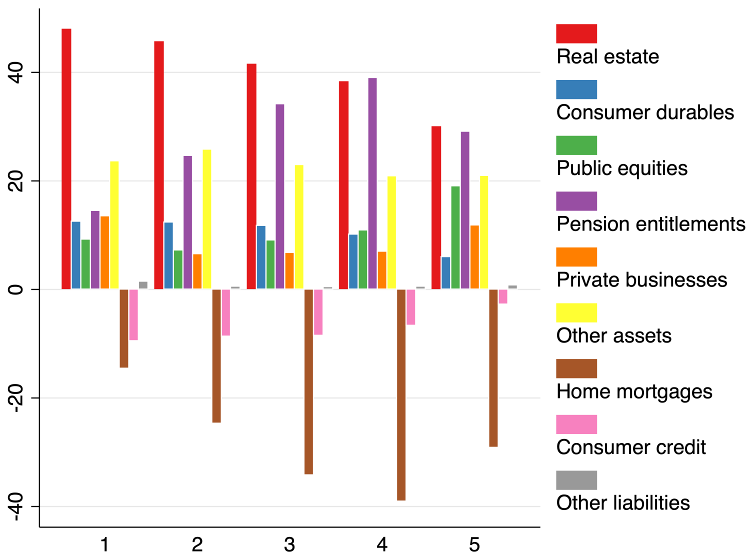
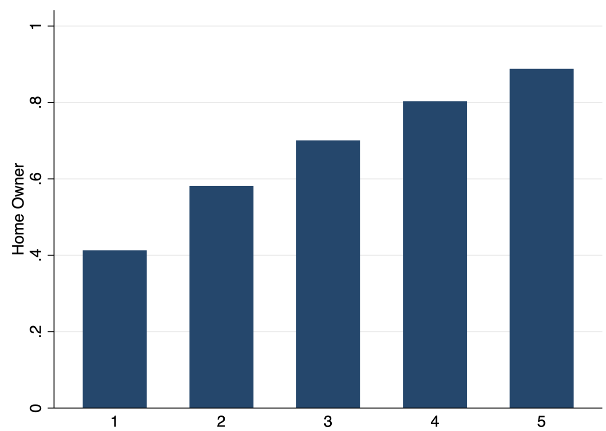
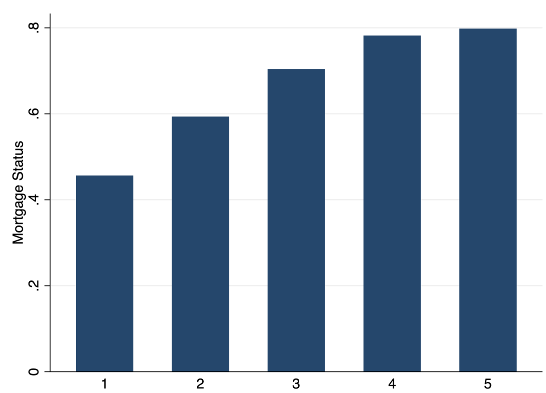


Figure IA.7: **Inflation Heterogeneity and Inflation Expectation Heterogeneity**

Figure (a) reports the share of home owners across income groups, between 2005 and 2019. The y-axis is between 0 and 1. The x-axis is income quintile. Figure (b) reports the share of households having a mortgage, conditional on being a home owner.



(a) Home Ownership across Income Quintiles



(b) Mortgage Status across Income Quintiles

Figure IA.8: **Correlation Between Inflation Expectation Gap and Chinese Yuan Exchange Rate**

This figure reports the monthly 12-month Chinese Yuan (RMB) appreciation relative to the US Dollar and the difference in the 3-month smoothed monthly 1-year forward inflation expectation between the bottom income households and the top income households based on the Michigan Survey of Consumers from 2005 through 2019. The correlation between RMB appreciation and the 1-year forward inflation expectation gap is 0.53.

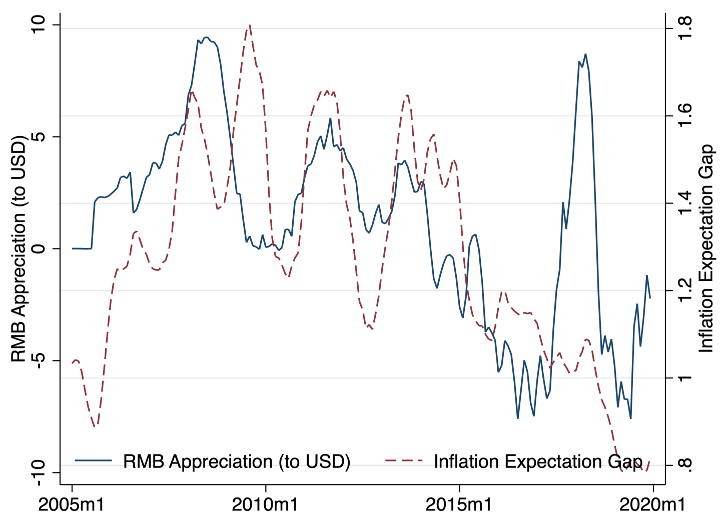


Figure IA.9: **Accumulated Inflation by Metropolitan Areas**

Figure IA.9 shows the accumulated increase in consumer price indexes since 2000 across major US metropolitan areas. The accumulated inflation in San Francisco increased by 67 percent, which in Detroit is only 40 percent. Data are from Bureau of Labor Statistics.

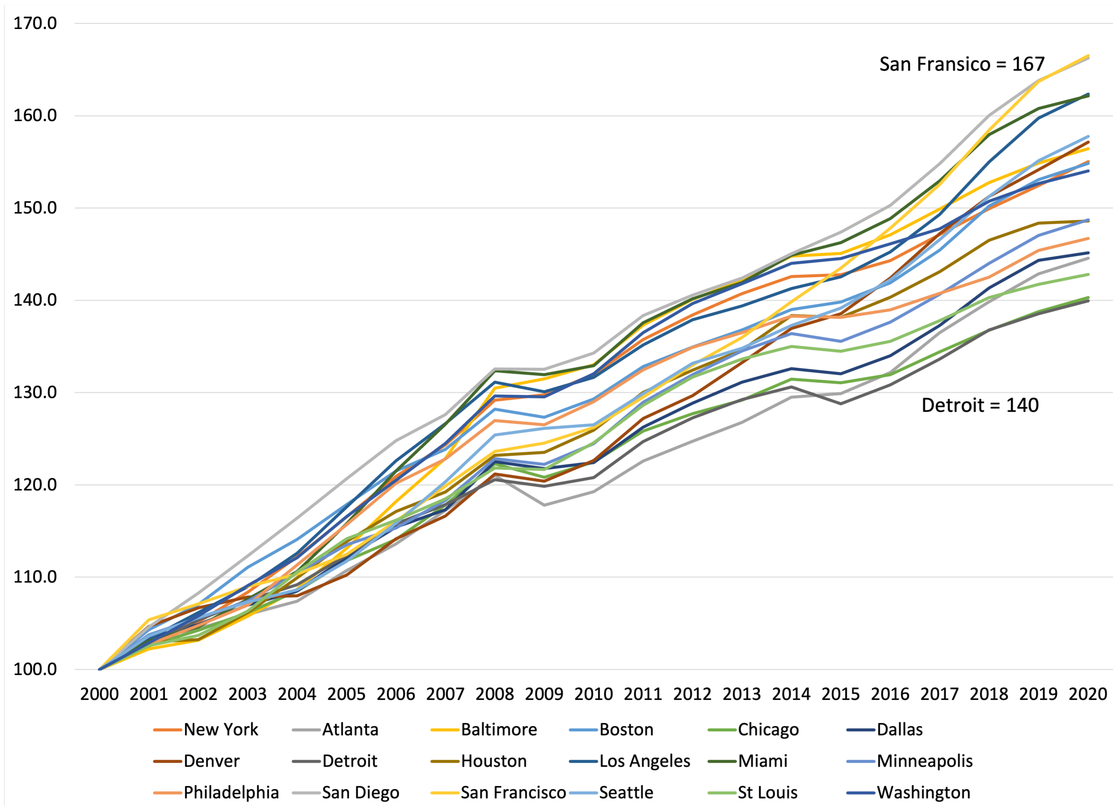


Figure IA.10: **Relative Inflation Spreads and Income Growth Spreads**

This figure reports the correlation between the relative nominal income growth spreads, estimated from the Annual Social and Economic Supplement (ASES) of the Current Population Survey, and relative inflation spreads, estimated from Nielsen Consumer Panel data, for US income quintiles between 2005 and 2019.

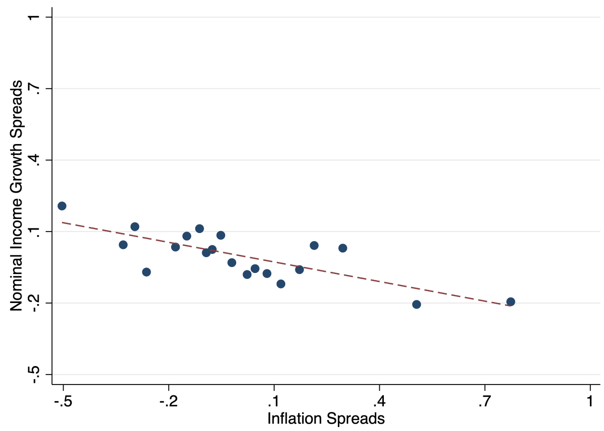


Table IA.1: **The Distribution of Buyers' Income Quintile and Locations' Income Quintile**

This table reports the percentage of mortgages in a census tract that belongs to income quintile j (columns) are taken by a buyer in income quintile i (rows), using mortgage level HMDA data between 2005 and 2017.

%	Property Census Tract Income Quintile				
Buyer Income Quintile	1	2	3	4	5
1	65.93	45.18	15.84	7.98	2.69
2	17.39	28.69	38.85	13.45	6.02
3	8.83	13.53	26.18	30.63	10.79
4	5.00	8.27	12.30	35.52	23.68
5	2.85	4.33	6.83	12.41	56.81
Total	100	100	100	100	100

Table IA.2: **Mortgage Borrowing and Inflation Heterogeneity**

$$\ln(Num_{k,j,c,t} + 1) = \beta \cdot \pi_{j,t} + \gamma \cdot X_{k,j,c,t} + \psi_{c,t} + \eta_k + \epsilon_{k,j,t}$$

where $Num_{k,j,c,t}$ is the number of mortgages originated at census tract k in year t. The average borrower in census tract k belongs to income quintile j in year t. And $\pi_{j,t}$ is the relative inflation spread of the income quintile j in year t. $\psi_{c,t}$ are the county by year fixed effects, and η_k are the census tract fixed effects. $X_{k,j,c,t}$ are other control variables of census tract k, including the log of median income, Zillow home value at the census tract, one-year local housing market return, 5-year housing market return, 1-year local rent growth, and local rent index. I also control for interest rate term structure and national inflation rate and allow heterogeneous sensitivity to those variables across income groups. The sample period is from 2005 to 2019. Column 5 has fewer observations because rent data have limited coverage. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	ln(Num + 1)			
$\pi_{j,t}$	0.0709*	0.0840**	0.0615*	0.0933***
	(0.0380)	(0.0344)	(0.0309)	(0.0325)
1-Year Housing Ret		0.561***	0.413***	0.542***
		(0.0947)	(0.0740)	(0.111)
5-Year Housing Ret		-0.0106***	-0.00835***	-0.0117***
		(0.00217)	(0.00174)	(0.00294)
1-Year Rent Growth				0.0864***
				(0.0291)
Observations	660,015	592,313	592,313	348,801
R-squared	0.897	0.899	0.903	0.912
Control Variables	Yes	Yes	Yes	Yes
Inflation Exposure			Yes	Yes
Interest Rate Curve Exposure			Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.3: **Mortgage Borrowing and Inflation Heterogeneity: After the Financial Crisis**

$$\ln(Num_{k,j,c,t}+1) = \beta \cdot \pi_{j,t} + \gamma \cdot X_{k,j,c,t} + \psi_{c,t} + \eta_k + \epsilon_{k,j,t}$$

where $Num_{k,j,c,t}$ is the number of mortgages originated at census tract k in year t. The average borrower in census tract k belongs to income quintile j in year t. And $\pi_{j,t}$ is the relative inflation spread of the income quintile j in year t. $\psi_{c,t}$ are the county by year fixed effects, and η_k are the census tract fixed effects. $X_{k,j,c,t}$ are other control variables of census tract k, including the log of median income, Zillow home value at the census tract, 1 year local housing market return, 5 year housing market return, 1 year local rent growth, and local rent index. I also control for interest rate term structure and national inflation rate, and allow heterogeneous sensitivity to those variables across income groups. The sample period is from 2010 to 2019. Column (2) and (5) have fewer observations because rent data have limited coverage. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	OLS	OLS	2SLS	2SLS
$\pi_{j,t}$	0.0543**	0.0477*	0.103***	0.113***
	(0.0231)	(0.0282)	(0.0320)	(0.0374)
1-Year Housing Ret	0.485***	0.561***	0.492***	0.573***
	(0.0704)	(0.0769)	(0.0699)	(0.0759)
5-Year Housing Ret	-0.00571***	-0.00751***	-0.00565***	-0.00739***
	(0.00175)	(0.00277)	(0.00174)	(0.00276)
1-Year Rent Growth		0.111***		0.112***
		(0.0306)		(0.0307)
Observations	413,315	255,640	413,315	255,640
R-squared	0.899	0.909	0.919	0.915
Inflation Exposure	Yes	Yes	Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.4: **Mortgage Borrowing and Inflation Heterogeneity: Robustness of Inflation Definition**

$$\ln(Num_{k,j,c,t} + 1) = \beta \cdot \pi_{j,t} + \gamma \cdot X_{k,j,c,t} + \psi_{c,t} + \eta_k + \epsilon_{k,j,t}$$

where $Num_{k,j,c,t}$ is the number of mortgages originated at census tract k in year t. The average borrower in census tract k belongs to income quintile j in year t. And $\pi_{j,t}$ is the relative inflation spread of the income quintile j in year t. $\psi_{c,t}$ are the county by year fixed effects, and η_k are the census tract fixed effects. $X_{k,j,c,t}$ are other control variables of census tract k, including the log of median income, Zillow home value at the census tract, 1 year local housing market return, 5 year housing market return, 1 year local rent growth, and local rent index. I also control for interest rate term structure and national inflation rate, and allow heterogeneous sensitivity to those variables across income groups. The sample period is from 2010 to 2019. Columns (1)-(5) compare the estimated coefficients of 5 versions of inflation index. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	ln(Num + 1)				
	(1)	(2)	(3)	(4)	(5)
	Tornqvist	Marshall	Fisher	Laspeyres	Paasche
$\pi_{j,t}$	0.0935***	0.0277**	0.0286**	0.0117	0.0387***
	(0.0324)	(0.0136)	(0.0137)	(0.00898)	(0.0145)
1-Year Housing Ret	0.541***	0.576***	0.575***	0.601***	0.549***
	(0.111)	(0.112)	(0.111)	(0.113)	(0.111)
5-Year Housing Ret	-0.0117***	-0.0118***	-0.0118***	-0.0117***	-0.0119***
	(0.00295)	(0.00292)	(0.00292)	(0.00288)	(0.00296)
1-Year Rent Growth	0.0874***	0.0933***	0.0933***	0.0982***	0.0907***
	(0.0288)	(0.0297)	(0.0297)	(0.0295)	(0.0301)
Observations	348,542	348,542	348,542	348,542	348,542
R-squared	0.897	0.897	0.897	0.897	0.897
Control Variables	Yes	Yes	Yes	Yes	Yes
Inflation Exposure	Yes	Yes	Yes	Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.5: **Home Ownership and Inflation Heterogeneity**

$$\text{Home Ownership}_{i,j,k,t} = \beta \cdot \pi_{j,t} + \gamma \cdot X_{i,j,k,t} + \psi_{k,t} + \eta_k + \epsilon_{k,t}$$

where Home Ownership$_{i,j,k,t}$ is a dummy variable that equals to one if household i reports as a homeowner. $\pi_{j,t}$ is the relative inflation spread of the income quintile j that household i belongs to in year t. $\psi_{k,t}$ are the county by year fixed effects, and η_k are the public use micro area (PUMA) fixed effects. $X_{i,j,k,t}$ are other control variables, including the log of household income, PUMA home value index, 1-year PUMA home value appreciation, 1-year PUMA rent growth, and PUMA rent index. I also control interest rate term structure and national inflation rate and allow heterogeneous exposure to those variables across income groups. The sample period is from 2005 to 2019. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Home Ownership			
$\pi_{j,t}$	0.0270***	0.0350***	0.0334***	0.0337***
	(0.00646)	(0.00633)	(0.00703)	(0.00706)
1-Year Housing Ret		-0.0100	-0.00962	-0.00951
		(0.00638)	(0.00635)	(0.00578)
1-Year Rent Growth				-0.00497
				(0.00884)
Observations	9,677,676	8,872,562	8,872,562	8,833,397
R-squared	0.224	0.221	0.221	0.221
Control Variables	Yes	Yes	Yes	Yes
Inflation Exposure			Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.6: **Home Ownership and Inflation Heterogeneity: After the Financial Crisis**

$$\text{Home Ownership}_{i,j,k,t} = \beta \cdot \pi_{j,t} + \gamma \cdot X_{i,j,k,t} + \psi_{k,t} + \eta_k + \epsilon_{k,t}$$

where Home $\text{Ownership}_{i,j,k,t}$ is a dummy variable that equals to one if household i reports as a homeowner. $\pi_{j,t}$ is the relative inflation spread of the income quintile j that household i belongs to in year t. $\psi_{k,t}$ are the county by year fixed effects, and η_k are the public use micro area (PUMA) fixed effects. $X_{i,j,k,t}$ are other control variables, including the log of household income, PUMA home value index, 1 year PUMA home value appreciation, 1 year PUMA rent growth, and PUMA rent index. I also control for interest rate term structure and national inflation rate, and allow heterogeneous exposure to those variables across income groups. The sample period is from 2010 to 2019. Column 5 has fewer observations because rent data have limited coverage. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Home Ownership			
	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
$\pi_{j,t}$	0.0314***	0.0317***	0.0636***	0.0639***
	(0.00646)	(0.00633)	(0.00703)	(0.00706)
1-Year Housing Ret	-0.0101	-0.00975	-0.0101	-0.00977
	(0.00834)	(0.00737)	(0.00830)	(0.00734)
1-Year Rent Growth		-0.00437		-0.00464
		(0.00956)		(0.00945)
Observations	6,535,834	6,502,583	6,535,834	6,502,583
R-squared	0.218	0.218	0.218	0.218
Inflation Exposure	Yes	Yes	Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.7: **Home Ownership and Inflation Heterogeneity: Robustness of Inflation Definition**

$$\text{Home Ownership}_{i,j,k,t} = \beta \cdot \pi_{j,t} + \gamma \cdot X_{i,j,k,t} + \psi_{k,t} + \eta_k + \epsilon_{k,t}$$

where Home Ownership$_{i,j,k,t}$ is a dummy variable that equals to one if household i reports as a homeowner. $\pi_{j,t}$ is the relative inflation spread of the income quintile j that household i belongs to in year t. $\psi_{k,t}$ are the county by year fixed effects, and η_k are the public use micro area (PUMA) fixed effects. $X_{i,j,k,t}$ are other control variables, including the log of household income, PUMA home value index, 1 year PUMA home value appreciation, 1 year PUMA rent growth, and PUMA rent index. I also control for interest rate term structure and national inflation rate, and allow heterogeneous exposure to those variables across income groups. The sample period is from 2010 to 2019. Columns (1)-(5) compare the estimated coefficients of 5 versions of inflation index. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Home Ownership				
	(1)	(2)	(3)	(4)	(5)
	Tornqvist	Marshall	Fisher	Laspeyres	Paasche
$\pi_{j,t}$	0.0337***	0.0118***	0.0118***	0.0101***	0.00624
	(0.00706)	(0.00331)	(0.00333)	(0.00277)	(0.00403)
1-Year Housing Ret	-0.00951	-0.0100*	-0.0100*	-0.00960	-0.0103*
	(0.00578)	(0.00586)	(0.00586)	(0.00585)	(0.00585)
1-Year Rent Growth	-0.00497	-0.00557	-0.00555	-0.00457	-0.00637
	(0.00884)	(0.00883)	(0.00883)	(0.00883)	(0.00894)
Observations	8,833,397	8,833,397	8,833,397	8,833,397	8,833,397
R-squared	0.221	0.221	0.221	0.221	0.221
Control Variables	Yes	Yes	Yes	Yes	Yes
Inflation Exposure	Yes	Yes	Yes	Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.8: **Correlation Between RMB Appreciation and US Inflation Gap**

$$\text{Inflation Gap}_t = \beta \cdot \text{RMB Appreciation}_t + \gamma \cdot X_t + \epsilon_t,$$

where Inflation Gap_t is the difference of the month-to-month inflation spreads between bottom income households and top income households, RMB Appreciation_t is the month-to-month Chinese Yuan (RMB) appreciation against US Dollar (USD). Column (1) shows that the positive correlation between RMB appreciation and the US inflation gap is statistically significant, with the F-statistic equal 45.86. In column (2), I control for potentially co-moving variables such as aggregate inflation rates, fed funds rates, gas price changes, and dollar index changes. In column (3), I add month fixed effects to absorb seasonality, and in column (4), I add year as a control variable to capture the linear long-run trend. Newey-West standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Inflation Gap			
RMB Appreciation	0.0734***	0.0731***	0.0734***	0.0731***
	(0.0173)	(0.0203)	(0.0178)	(0.0210)
Observations	180	180	180	180
Controls		Yes		Yes
Month Fixed Effects			Yes	Yes
Newey-West Standard Errors	Yes	Yes	Yes	Yes

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.9: **Home Ownership and Inflation Heterogeneity: RMB Appreciation as IV**

The second stage equation and the first stage in the IV specifications are

$$\text{Home Ownership}_{i,j,k,t} = \beta \cdot \hat{\pi_{j,t}} + \gamma \cdot X_{i,j,k,t} + \psi_{k,t} + \eta_k + \epsilon_{i,j,k,t}$$
$$\pi_{j,t} = \tilde{\beta}_j \cdot \mathbf{Z_t} + \tilde{\alpha},$$

where Home Ownership$_{i,j,k,t}$ is a dummy variable that equals to one if household i reports as a home owner. $\pi_{j,t}$, the relative inflation spread of group j in year t, is instrumented by Z_t = RMB Appreciation$_t$, which is the appreciation of the Chinese Yuan relative to the US dollar over the past 12 months. $\psi_{k,t}$ are the county by year fixed effects, and η_k are the public use micro area (PUMA) fixed effects. $X_{i,j,k,t}$ are other control variables, including the log of household income, PUMA home value index, 1 year PUMA home value appreciation, 1 year PUMA rent growth, and PUMA rent index. I also control for interest rate term structure and national inflation rate, and allow heterogeneous exposure to those variables across income groups. The sample period is from 2005 to 2019. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Home Ownership			
$\widehat{\pi_{j,t}}$	0.0756***	0.0800***	0.0905***	0.0909***
	(0.0143)	(0.0142)	(0.0165)	(0.0165)
1-Year Housing Ret	-0.00914	-0.00914	-0.00931	-0.00926
		(0.00626)	(0.00626)	(0.00571)
1-Year Rent Growth				-0.00497
				(0.00867)
Observations	9,677,676	8,872,562	8,872,562	8,833,397
R-squared	0.224	0.221	0.221	0.221
Control Variables	Yes	Yes	Yes	Yes
Inflation Exposure			Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.10: **Inflation Expectation Heterogeneity and the 2005 Chinese Yuan Reform**

The regression uses the disaggregated monthly household expectation interviews from Michigan Surveys of Consumers from 2003 to 2007.

$$\text{Expectation}_{i,m,t} = \beta \cdot \text{Bottom}_{i,t} \cdot \text{Reform}_t + \gamma \cdot X_{i,m,t} + \eta \cdot Z_{i,m,t} + \psi_{m,t} + \epsilon_{i,m,t},$$

where $\text{Expectation}_{i,m,t}$ is the inflation or income expectation of survey participant i in year-month t at region m, the dummy variable $\text{Bottom}_{i,t}$ equals to one if the participant i is at the bottom income quintile, and Reform_t is a dummy variable indicating whether t is after the 2005 July Chinse Yuan reform. $X_{i,m,t}$ are the participant's demographic characteristics, including income, gender fixed effects, education fixed effects, age fixed effects, and birth year fixed effects. Moreover, I also control $Z_{i,m,t}$, which are participants' expectations of future unemployment and aggregate economy to make sure other expectations do not drive the result. $\psi_{i,m,t}$ are the region by year by month fixed effects to absorb any aggregate and local economy variations. Columns (1)-(2) show results for 1-year forward inflation expectation. Columns (3)-(4) show results for 5-year forward inflation expectation. And Columns (5)-(6) are income expectations. Standard errors double clustered at the year-month level and birth year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	1 Year Inflation		5 Year Inflation		Income	
Bottom · RMB Reform	0.167**	0.162**	0.118**	0.151***	0.137	-0.0520
	(0.0806)	(0.0714)	(0.0509)	(0.0538)	(0.631)	(0.655)
Constant	3.571***	3.581***	3.314***	3.306***	5.354***	5.417***
	(0.0259)	(0.0228)	(0.0143)	(0.0152)	(0.225)	(0.228)
Observations	24,244	23,578	23,942	23,348	26,009	25,195
R-squared	0.086	0.135	0.063	0.081	0.086	0.099
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Income Quintile-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Macro Expectation Controls	No	Yes	No	Yes	No	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.11: **Household Expectation and the 2005 Chinese Yuan Reform**

The regression uses the disaggregated monthly household expectation interviews from Michigan Surveys of Consumers from 2003 to 2007.

$$\text{Expectation}_{i,m,t} = \beta \cdot \text{Bottom}_{i,m,t} \cdot \text{Reform}_t + \gamma \cdot X_{i,m,t} + \eta \cdot Z_{i,m,t} + \psi_{m,t} + \epsilon_{i,m,t},$$

where $\text{Expectation}_{i,t}$ is the household i's expectation of the future macro economy at year-month t, the dummy variable $\text{Bottom}_{i,t}$ equals to one if the participant i is at the bottom income quintile, and Reform_t is a dummy variable indicating whether t is after the 2005 July Chinse Yuan reform. $X_{i,m,t}$ are the participant's demographic characteristics, including income, gender fixed effects, education fixed effects, age fixed effects, and birth year fixed effects. $\psi_{i,m,t}$ are the region by year by month fixed effects to absorb any aggregate and local economy variations. Column (1) show results for future gas price, and column (2) for the future unemployment rate. Columns (3)-(4) test the 1 and 5 year forward macro economy conditions respectively. Standard errors double clustered at the year-month level and birth year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	Gas Price	Unemployment Rate	1 Year Economy	5 Year Economy
Bottom · RMB Reform	2.305	0.0211	-0.0453	0.00782
	(2.613)	(0.0452)	(0.0495)	(0.0529)
Constant	52.81***	2.629***	2.986***	3.137***
	(1.259)	(0.0166)	(0.0169)	(0.0182)
Observations	19,042	26,754	25,206	25,967
R-squared	0.097	0.081	0.102	0.095
Demographic Controls	Yes	Yes	Yes	Yes
Birth Year Fixed Effects	Yes	Yes	Yes	Yes
Income Quintile-Year Fixed Effects	Yes	Yes	Yes	Yes
Region-Year-Month Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.12: **Mortgage Borrowing and the Chinese Yuan Reform**

$$\ln(Num_{k,c,t} + 1) = \beta \cdot \text{Bottom}_k \cdot \text{Reform}_t + \gamma \cdot X_{k,c,t} + \psi_{k,t} + \eta_{k,t} + \xi_{k,t} + \epsilon_{k,c,t}$$

where $Num_{k,c,t}$ is the number of mortgages originated at zip code k in year-month t. Bottom_k is a dummy variable and equals one if zip code k belongs to the bottom income quintile. Reform_t is also a dummy variable and equals to one if year-month t is after the RMB Reform in July 2005. $\psi_{c,t}$ are the county by year by month fixed effects, $\eta_{k,t}$ are the zip code by year fixed effects, $\xi_{k,t}$ are the zip code by month fixed effects. $X_{k,c,t}$ are other control variables, like last month's home value at the zip code and one year local home value appreciation. By including county-by-year-by-month fixed effects, I can tightly control for any county-level time-varying macroeconomic variations. With zip code by year fixed effects, I can control for the long-run variations at a zip code level associated with the housing market boom and bust between 2003 and 2007. The zip code-by-month fixed effects are further used to control seasonality variations in the zip code level housing markets. In columns (2) and (4), I control for the share of private labeled securtization (PLS) mortgages among all mortgages and the share of mortgages with misreported owner occupancy and second lien among all PLS mortgages, at the zip code by month level. The sample period is from 2003 to 2007. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	log(Number + 1)			
	(1)	(2)	(3)	(4)
Bottom Qunitile · RMB Shock	0.0356**	0.0341**	0.0373**	0.0355**
	(0.0166)	(0.0165)	(0.0166)	(0.0165)
PLS Share			-0.188***	-0.212***
			(0.00995)	(0.00910)
Misreporting Share		0.0855***		0.114***
		(0.00622)		(0.00722)
Observations	402,982	402,982	402,982	402,982
R-squared	0.939	0.940	0.940	0.940
Control Variables	Yes	Yes	Yes	Yes
ZipCode-Year Fixed Effects	Yes	Yes	Yes	Yes
ZipCode-Month Fixed Effects	Yes	Yes	Yes	Yes
Year-Month-County Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.13: **Home Ownership within a Group and Inflation Heterogeneity**

$$\text{Home Ownership}_{i,j,k,t} = \beta \cdot \pi_{j,t} + \gamma \cdot X_{i,j,k,t} + \psi_{k,t} + \eta_k + \epsilon_{k,t}$$

where Home Ownership$_{i,j,k,t}$ is a dummy variable that equals to one if household i reports as a homeowner. Higher is a dummy variable equals to one if household i is at the top half of income distribution within group j. Young is a dummy variable equals to one if household i is below 40 years ago. $\pi_{j,t}$ is the relative inflation spread of the income quintile j that household i belongs to in year t. $\psi_{k,t}$ are the county by year fixed effects, and η_k are the public use micro area (PUMA) fixed effects. $X_{i,j,k,t}$ are other control variables, including the log of household income, PUMA home value index, 1-year PUMA home value appreciation, 1-year PUMA rent growth, and PUMA rent index. I also control interest rate term structure and national inflation rate and allow heterogeneous exposure to those variables across income groups. The sample period is from 2005 to 2019. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Home Ownership			
$\pi_{j,t}$	0.0612***	0.0711***	0.0674***	0.0679***
	(0.0117)	(0.0116)	(0.0132)	(0.0132)
Higher	0.0322***	0.0340***	0.0342***	0.0343***
	(0.00330)	(0.00321)	(0.00326)	(0.00327)
$\pi_{j,t} \cdot$ Higher	0.0150**	0.0192***	0.0195***	0.0193***
	(0.00689)	(0.00640)	(0.00634)	(0.00634)
$\pi_{j,t} \cdot$ Young	-0.136***	-0.142***	-0.141***	-0.141***
	(0.0276)	(0.0278)	(0.0278)	(0.0278)
1-Year Housing Ret		-0.0111*	-0.0107*	-0.00996*
		(0.00593)	(0.00589)	(0.00540)
1-Year Rent Growth				-0.00898
				(0.00769)
Observations	9,677,676	8,872,562	8,872,562	8,833,397
R-squared	0.224	0.221	0.221	0.221
Control Variables	Yes	Yes	Yes	Yes
Inflation Exposure			Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.14: **Detailed Distribution of Household Types**

This table shows the detailed distribution of households based on their locations and their home ownership status under two inflation heterogeneity scenarios. In the first scenario, relative inflation spreads are zero for both high income households and low income households. In the second scenario, the relative inflation spread is 0.3pp for low income groups and -0.3pp for high income households. Numbers reported are percentages of each type of households in the economy.

	Home Owner Status in Inflation Heterogeneity Scenarios		Island	
			High Income	Low Income
Income Group	No	Yes	%	%
High	Owner	Owner	33.6	10.0
	Owner	Renter	28.6	0
	Renter	Owner	0	0
	Renter	Renter	1.9	0
Low	Owner	Owner	0	28.6
	Owner	Renter	0	0
	Renter	Owner	1.8	9.6
	Renter	Renter	8.2	1.9

Table IA.15: **Mortgage Borrowing and Inflation Heterogeneity: China Trade Exposure**

The second stage equation and the first stage in the IV specifications are

$$\ln(Num_{k,j,c,t} + 1) = \beta \cdot \hat{\pi}_{j,t} + \gamma \cdot X_{k,j,c,t} + \psi_{c,t} + \eta_k + \epsilon_{k,j,c,t},$$
$$\pi_{j,t} = \tilde{\beta}_j \cdot \mathbf{Z_t} + \tilde{\alpha},$$

where k indexes census tract, t the year, $Num_{k,j,c,t}$ is the number of mortgages originated at census tract k in year t recorded by HMDA. $\pi_{j,t}$, the relative inflation spread of income quintile j in year t, is instrumented by Z_t = RMB Appreciation$_t$, which is the appreciation of the Chinese Yuan relative to the US dollar over the past 12 months. $\psi_{c,t}$ are the county by year fixed effects, and η_k are the census tract fixed effects. $X_{k,j,c,t}$ are other control variables of census tract k, including the log of median income, Zillow home value at the census tract, 1-year local housing market return, 5-year housing market return, 1-year local rent growth, and local rent index. I also control for short term and long term interest rates and national inflation rate and allow heterogeneous sensitivities to those variables across income groups. The sample period is from 2005 to 2019. Columns (1) and (2) are run on the subsample of low China trade exposure counties, and Columns (3) and (4) are run on the subsample of high China trade exposure counties. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Low Trade Exposure	Low Trade Exposure	High Trade Exposure	High Trade Exposure
$\widehat{\pi_{j,t}}$	0.213***	0.197***	0.180***	0.155***
	(0.0532)	(0.0549)	(0.0458)	(0.0480)
1-Year Housing Ret	0.353***	0.481***	0.511***	0.633***
	(0.0636)	(0.0904)	(0.112)	(0.165)
1-Year Rent Growth		0.0861*		0.0906**
		(0.0503)		(0.0366)
Observations	285,559	153,443	302,507	193,720
R-squared	0.904	0.906	0.908	0.910
Inflation Exposure	Yes	Yes	Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.16: **Home Ownership and Inflation Heterogeneity: China Trade Exposure**

The second stage equation and the first stage in the IV specifications are

$$\text{Home Ownership}_{i,j,k,t} = \beta \cdot \hat{\pi_{j,t}} + \gamma \cdot X_{i,j,k,t} + \psi_{k,t} + \eta_k + \epsilon_{i,j,k,t}$$
$$\pi_{j,t} = \tilde{\beta}_j \cdot \mathbf{Z_t} + \tilde{\alpha},$$

where Home Ownership$_{i,j,k,t}$ is a dummy variable that equals to one if household i reports as a home owner. $\pi_{j,t}$, the relative inflation spread of group j in year t, is instrumented by Z_t = RMB Appreciation$_t$, which is the appreciation of the Chinese Yuan relative to the US dollar over the past 12 months. $\psi_{k,t}$ are the county by year fixed effects, and η_k are the public use micro area (PUMA) fixed effects. $X_{i,j,k,t}$ are other control variables, including the log of household income, PUMA home value index, 1 year PUMA home value appreciation, 1 year PUMA rent growth, and PUMA rent index. I also control for interest rate term structure and national inflation rate, and allow heterogeneous exposure to those variables across income groups. The sample period is from 2005 to 2019. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) Low Trade Exposure	(2) Low Trade Exposure	(3) High Trade Exposure	(4) High Trade Exposure
$\widehat{\pi_{j,t}}$	0.0995***	0.0995***	0.0822***	0.0831***
	(0.0183)	(0.0184)	(0.0154)	(0.0155)
1-Year Housing Ret	-0.00836	-0.00958	-0.00954	-0.0101*
	(0.00708)	(0.00729)	(0.00657)	(0.00595)
1-Year Rent Growth	-0.00921			-0.00181
	(0.00851)			(0.0115)
Observations	4,438,346	4,451,946	4,384,161	4,358,596
R-squared	0.252	0.243	0.251	0.244
Inflation Exposure	Yes	Yes	Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.17: **Mortgage Lien Status and Inflation Heterogeneity**

$$\text{Mortgage Lien}_{i,j,k,t} = \beta \cdot \pi_{j,t} + \gamma \cdot X_{i,j,k,t} + \psi_{k,t} + \eta_k + \epsilon_{i,j,k,t}$$

where Mortgage $\text{Lien}_{i,j,k,t}$ is a dummy variable that equals to one if household i reports having a first lien or home equity mortgage. $\pi_{j,t}$ is the income-specific inflation of the income quintile j that household i belongs to in year t. $\psi_{k,t}$ are the county by year fixed effects, and η_k are the public use micro area (PUMA) fixed effects. $X_{k,t}$ are other control variables, including the log of household income, PUMA home value index, 1-year PUMA home value appreciation, 1-year PUMA rent growth, and PUMA rent index. I also control interest rate term structure and national inflation rate and allow heterogeneous sensitivity to those variables across income groups. The sample period is from 2005 to 2019. Standard errors clustered at the county level and income quintile by year level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	2005-2019		2010-2019	
	(1)	(2)	(3)	(4)
	First	Second (Home Equity)	First	Second (Home Equity)
$\pi_{j,t}$	0.0394***	-0.0234***	0.0738***	-0.00711
	(0.0105)	(0.00525)	-0.00627	(0.00782)
1-Year Housing Ret	-0.00560	-0.00239	-0.00562	-0.00238
	(0.00591)	(0.00223)	(0.00588)	(0.00222)
1-Year Rent Growth	-0.00538	0.00122	-0.00340	0.00128
	(0.00543)	(0.00384)	(0.00542)	(0.00383)
Observations	8,872,562	8,833,397	6,535,834	6,502,583
R-squared	0.191	0.069	0.184	0.049
Inflation Exposure	Yes	Yes	Yes	Yes
Interest Rate Curve Exposure	Yes	Yes	Yes	Yes
County-by-Year Fixed Effects	Yes	Yes	Yes	Yes
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
Clustered Standard Errors	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1