Mobility and Housing: Cash-based Resettlement in China's Shantytown Renovation*

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Abstract

This paper investigates the impact of the shantytown renovation program with cash-based resettlement during 2015-18 on the housing market in China. As the program involves cash compensation to displaced households and land redevelopment, it increases both housing demand and supply. However, demand increases for both local and external markets as money flows to other cities not only through existing migration network but also by increasing additional household intercity migration, typically from lower- to top- tier cities, while supply only increases in the local market. Cities conducting the program ended up with lower housing prices and more severe supply overhang while those receiving the migrants experienced higher housing price growth, lower inventory and more housing speculation. The quantitative spatial model shows that money flow enlarges the gap in housing price growth from 2015 to 2020 between top- and lower-tier cities by 11.1%.

Keywords: shantytown renovation, migration, real estate price, housing speculation.
JEL classifications: D1, D5, G0, R0.

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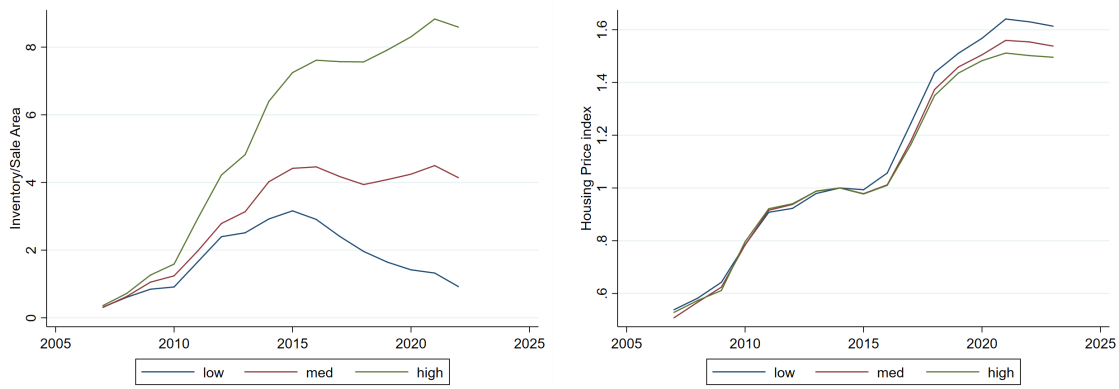
1 Introduction

Shanty towns are areas characterized by shabby houses, poor public facilities and harsh living conditions. Shantytown renovation, or sometimes also referred to as slum upgrading by UN Habitat in case the structures are not formal housing, is an essential part of urban development in many countries.[1] Typically, shantytown renovation first involves resettlement of incumbent residents and then the reconstruction of public facilities and residential and commercial properties. It is hence closely related to the real estate market in terms of both supply and demand. In this paper, we examine one of the largest-scale shantytown renovation program in the world that was conducted in China and study how it has shaped the spatial variation and dynamics of the housing market in China.

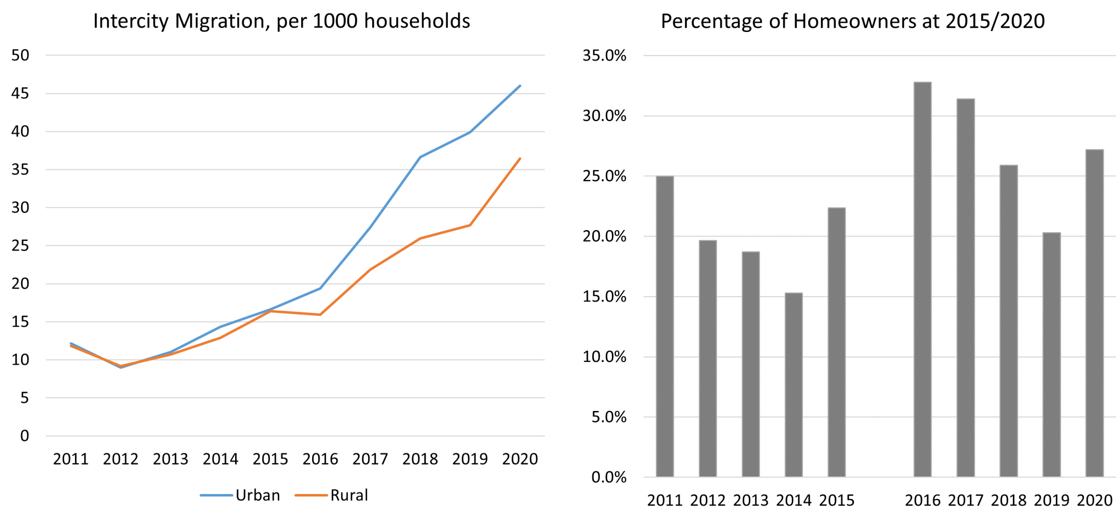
The shantytown renovation program has been a key part of the central government policy agenda since 2013, with the goal of renovating over 10 million units of various types of shanty homes in the urban area. Since its initiation, in-kind-based resettlement (or property exchange) used to be the dominant approach that the program adopted to compensate displaced residents. In 2015 when the housing inventories reached an unprecedentedly high level in lower-tier cities, the in-kind-based resettlement was partially replaced by cash-based resettlement which offers cash compensation to displaced residents so that they can buy homes from the housing market. The accumulated value of cash-based resettlement during 2015-2018 is more than four trillion RMB, compared to the net issuance of residential mortgages of 21.4 trillion RMB during 2016-2020. It is believed by the authority and many others that the cash-based resettlement has resolved the inventory overhang in lower-tier cities and contributed to the housing boom since 2015.[2]

As motivation, in Figure 1 we sort cities into three groups based on the accumulated cash-based resettlement of the program. In Panel (a), the left graph shows that the scale of the cash-based resettlement increases monotonically with the level of housing inventories held by home developers in 2014, consistent with the target of the policy. However, contrary to the common perception, the cities that received more intensive treatment experienced less response. After 2014, it is not the cities with the largest but

[1]See the report by UN Habitat.
[2]See the report from Reuters.



(a) Housing and Land Inventories and Housing Price



(b) Intercity Household Migration and Home ownership

Figure 1: The Shantytown Renovation Program and Household Migration

Note: The first figure plots the cities' average land and home inventories held by home developers scaled by their home sale area in 2014 and their housing prices normalized to be one in 2014. For each province, we divide cities equally into three groups based on the accumulated value of cash-based resettlement scaled by housing market transaction value in 2014. The second figure plots the number of intercity migration by urban and rural households for every 1000 urban households, and the fraction of urban immigrant households that are local homeowners in 2015 (2020) conditional on their migration year as shown in the horizontal axis.

those with the smallest scale of the cash-based resettlement that experienced the most dramatic drop in housing inventories and the largest increase in housing prices. At the same time, in Panel (b) the left graph shows that the number of intercity urban household migration has accelerated since 2015. The migration of rural households who are not targeted by the program followed the previous trend. Furthermore, the right graph in Panel (b) shows that the percentage of these intercity urban migrants who own houses in residence cities in 2020 is significantly higher than that in 2015, regardless of whether they arrive in 2020 (2015) or other years as shown on the horizontal axis. Taken all these empirical patterns as a whole, it is likely that the accelerated intercity migration and higher migrant home ownership are due to the spatial mismatch between the program treatment and the market responses.

Indeed, we find that cash-based resettlement, which essentially unlocked households from the illiquid housing market, allows for money flow not only through the existing migration network but also by facilitating household intercity migration. This has led to a rising housing demand in the destination cities and worsened the housing demand in the originating cities. As the program also results in a net increase of housing supply, cities conducting the program with cash-based resettlement—which are mostly lower-tier cities—ended up with lower housing prices and more severe supply overhang. In contrast, those cities that attracted migrants, which are mostly top-tier cities, experienced faster housing price growth, lower inventory and more housing speculation.

We start by measuring the scale of the cash-based resettlement at the city level. The cash-based resettlement are primarily financed by the so-called shantytown renovation loans granted by China Development Bank (hereafter referred to as "CDB loans").[3] For each city, we aggregate all individual CDB loans granted to finance shantytown renovation projects in that city. These cities can be viewed as originating cities, and we scale the total CDB loan in a city by its total house transaction value in 2014 to obtain *loan_orig*. For cities as destination cities that get exposed to the program conducted in other originating cities through household migration network, we construct a Bartik-style variable. More specifically, we calculate the amount of cash compensation per urban household at the originating cities times the number of urban migrant households from the originating to the destination city by 2015, and then summing them across all originating cities. We then scale this number by the 2014 total house transaction value in that destination

[3] China Agricultural Development Bank also provided loans for the cash-based resettlement, which is about 1/5 of CDB loans.

city, and call the resulting measure *loan_dest*.

In the first part of the paper, we conduct regression analysis to examine how the cash-based resettlement—which is measured by *loan_orig* and *loan_dest*—affects the city-level housing prices, housing supply, and level of inventories since 2015. Taking the year of 2014, which is right before the wide use of cash-based resettlement, as the base year, we conduct the standard Difference-in-ifference (DID) analysis with $(loan\_orig, loan\_dest)$ as two treatment variables. Throughout, we allow for province-by-year fixed effect to absorb potentially time-varying province-level shocks.

First, the housing prices in all cities exhibited parallel trend before 2015 across originating or destination cities, regardless of their exposure to cash-based resettlement. Since 2015, the housing prices started to diverge across cities with differential treatment. As originating cities, *loan_orig* had a significantly negative impact while as destination cities, *loan_dest* had a significantly positive impact on the cities' housing price growth after 2015.

Second, the residential land supply of all cities also exhibited parallel trend before 2015, regardless of the extent of exposure to cash-based resettlement as originating or destination cities. Since 2015, cities with higher *loan_orig* experienced an increase of residential land supply, with the magnitude of effect peaking in 2018 and then diminishing gradually to zero by 2022. In contrast, cities with *loan_dest* did not experience any difference in residential land supply, despite that their housing prices went up significantly.

Taking the above two facts together, we interpret the positive effect of *loan_dest* as increased housing demand by immigrants as they receive cash compensation from their originating cities. We interpret the negative effect of *loan_orig* as the program led to a higher local housing supply while some cash compensation flowed out of the originating cities. Housing supply increased following the program as the local governments demolish those shanty houses and supply the land to the market, from which real estate developers typically build houses with a greater capacity.[4]

Third, the net increase of housing supply together with household intercity migration

[4]We calculate the ratio between the floor area of the accumulated increase of residential land supply and the floor area of demolished houses to be about 2.13:1.59, suggesting that the local shantytown renovation program has led to a net increase of housing supply in the long run.

have important implications on the level of housing inventories. We calculate the city-level home inventories at the beginning of each year based on the difference between accumulated residential land supply and accumulated housing sale. When scaling it by the city's housing sale area in 2014, we find that housing inventories in cities with larger *loan_orig* continued to grow faster since 2015. In contrast, for cities with larger *loan_dest*, while there was no difference in their change of inventories as compared to cities with lower *loan_dest* before 2014, their level of housing inventories gradually decreased over time. In 2022, the increase of *loan_orig* from 0 to its mean is associated with an increase of housing inventories by 2.03 relative to housing sale area in 2014, while the increase of *loan_dest* from 0 to its mean is associated with a decrease of housing inventories by 0.53 relative to housing sale area in 2014.

We move on to explore the core of this paper: the reallocation of money through the migration network. Such reallocation can occur not only through the existing migration network but also by encouraging additional household intercity migration. We find evidence supporting both channels.

First, conditional on urban households who have left their originating cities by 2015, a larger size of cash-based resettlement in their originating cities predicts a higher fraction of households owning homes in the destination cities in 2020, and the increased home ownership is all driven by home purchases made after 2015. This supports the hypothesis that money flowed through existing network in 2015 and helped these migrant households to purchase local homes.

Second, using the DID estimation specification, we find that more households receiving the cash compensation in the originating city is associated with more urban household intercity migration since 2015, with the magnitude gradually increase over time, while there is no such difference before 2015. This pattern supports the hypothesis that the cash-based resettlement facilitate urban household intercity migration. As these household migrate, they took the cash compensation and spend on consumption and housing in other cities.

We also provide some suggestive evidence on the existence of housing speculation that is triggered by the cash-based resettlement as it has generated large and persistent housing price movements. First, we find that *loan_orig* (*loan_dest*) has a significant and negative (positive) treatment effect on the housing price-to-rent ratio after 2014. As the price-to-rent ratio is positively related to the household expectation of future price growth, the result implies that the home sellers expect the price growth induced by the cash-based resettlement to continue in the future. Second, using the household survey data, we find that the local households' intention to purchase homes decreases with *loan_orig* and increases with *loan_dest* since 2015, with the same sign as the effect on local housing prices. This pattern can be rationalized with speculation: after observing an increase of housing prices, they are more willing to purchase houses as they anticipate the price growth trend to continue. Third, using the residential mortgage foreclosure data, we find that the foreclosure prices, which only depends on buyers' belief about the housing market, started to revert the previous trend since 2021. This suggests a partial correlation of the previous trend. Furthermore, we find a significantly higher mortgage foreclosure rate in cities with higher *loan_dest* after 2021, consistent with the speculation of local households before 2021.

In the second part of the paper, we develop and estimate a spatial general equilibrium model to quantify the effects of the cash-based resettlement on the spatial variation and dynamics of housing prices. There are two periods in the model. In each period, a group of urban and rural households need to make migration decisions. Cities differ in terms of the prevailing level of wages and housing prices. Each urban household is endowed with one unit of house in his/her originating city and intercity migration can only occur after the household successfully sell his/her endowed houses with a given probability. After migration, households earn local wages and spend on consumption and local houses. On top of these features, there is a reallocation cost and household-specific location preference, and housing prices and household migration will be jointly determined in equilibrium. We take other variables such as wages as exogenous.

We introduce the shantytown renovation program with cash-based resettlement, which is not anticipated, in the second period. The program generates two effects. The first is to increase the liquidity of the second-hand housing market as the governments act as buyers in the market. The second is the creation of new housing supply. That is, by demolishing shanty houses, the government will be able to supply the residential land to the housing market.

We characterize the counterfactual changes by a system of equations containing changes of both endogenous and exogenous variables in period two relative to period one, constant elasticities, and baseline equilibrium shares in period one, a formula known as "exact hat algebra" in the trade literature (Costinot and Rodríguez-Clare, 2014; Dingel and Tintelnot, 2021). More specifically, we take period one as 2011-2015 and estimate the migration elasticities and the model-implied housing market liquidity using observed migration network in 2011-2015. We then take period two as 2016-2020, and extrapolate the housing supply and size of urban/rural households in period two by projecting the observed values during 2016-2020 onto the corresponding values in 2011-2015 and use the predicted values as model inputs.[5]

Our quantitative model matches the data quite well in terms of capturing the effect of the cash-based resettlement. Regressing the observed and model-predicted home price growth on $(loan\_orig, loan\_dest)$ generates quantitatively similar coefficient estimates. Regressing the observed and model-predicted housing price growth on the city's initial housing prices before 2015 also generates quantitatively similar results.

Overall, the model predicts that the aggregate effect of the cash-based resettlement on housing prices is small relative to the increase of housing prices in the data. On average, the introduction of cash-based resettlement increases the housing prices only by 4.70% or 378.39 RMB per square meter. In contrast, the average housing price growth from period one to period two is 38.0% in the data.

In contrast, the spatial variation of the effect of the cash-based resettlement is considerable. The model predicts not only i) a negative correlation between the size of cash-based resettlement at the originating cities and its housing price growth, an empirical pattern we have discussed above, but also ii) a positive correlation between the city's housing prices before 2015 and subsequent housing price growth, a fact that is shown in Table 5 in Section 5.

Indeed, when we sort cities into ten groups based on their initial housing prices, the model predicts a housing price growth of about 30% for the bottom group and almost

[5]As pointed out by Dingel and Tintelnot (2021), in granular setting with sparse migration matrix, the quantitative results may be sensitive to whether we use observed or model-predicted data to calculate the baseline equilibrium shares. We report results using the observed data in the paper. Using model-predicted data makes little difference in our context.

50% for the top group. This is due to endogenous money flows across cities, as our model predictts that only the top two groups consisting of 59 cities are net inflow of CDB loans due to household immigration. The bottom four groups had a net loss of about 30% relative to the amount originated in the cities.

To quantify how much money flow and household migration contributed to the price dispersion across cities, we consider an alternative to the cash-based resettlement – the "voucher-based resettlement," which has been adopted in a few cities over the years. Under this scheme, households receive a voucher which can only be used to purchase houses in their local (originating) cities. The model predicts that under the voucher-based resettlement, the correlation between the size of the resettlement and the housing price growth at the originating cities becomes positive, and the gap in housing price growth between the top and bottom city groups becomes 9% as compared to 20% under the cash-based resettlement.

Literature Review Our paper is related to several strands of literature. First, our paper contributes to the literature on the impact of inter-city network linkages, particularly migration flows, on the housing market.[6] Gyourko et al. (2013) demonstrate that significant long-term differences in average house price appreciation across U.S. metropolitan areas can be attributed to the concentration of high-income households in cities with inelastic land supply. This scarcity drives up house prices and price-to-rent ratios, effectively crowding out lower-income households. Howard (2020) observes that within-US migration leads to a decrease in the unemployment rate in destination cities over several years, driven by increased housing demand from new residents, which in turn stimulates construction jobs and boosts house prices. Glaeser et al. (2012) suggest that accounting for migration can diminish the influence of interest rates on house prices, reflecting the role of households' endogenous migration decisions. Chinco and Mayer (2016) find that the demand from out-of-town second-home buyers can predict both house price appreciation and mispricing during the mid-2000s. Schubert (2021) identifies the network effect on house prices resulting from migration between U.S. cities. The paper shows that

[6] Besides migration flows, other forms of inter-city network linkages can also have significant impact on house prices, such as Bailey et al. (2018) (social media networks) and Howard et al. (2023) (remote work networks).

exogenous shocks that increase house prices in one city can drive emigration to other cities, subsequently raising house prices in the destination cities.

These studies primarily focus on how the housing markets in destination cities respond to migration, without exploring the origins of these migrations. By contrast, our study delves into the endogenous migration decisions prompted by shantytown renovation programs, examining the endogenous response of house prices in both the cities that receive immigrants and those that send out emigrants.

Second, our paper aligns with a substantial body of work examining regional disparities in house price growth, which can be largely attributed to variations in housing supply and demand. Mian and Sufi (2009) emphasize the critical role of housing supply elasticity in driving regional house price disparities (see also Mian and Sufi, 2011 and Mian, Rao, and Sufi, 2013). The demand-side perspective attributes regional house price variations to location-specific demand shocks. Himmelberg et al. (2005) correlate house price adjustments with underlying economic fundamentals. Van Nieuwerburgh and Weill (2010) show that cross-sectional productivity differences determined the dispersion of house prices across US metropolitan areas. Howard and Liebersohn (2023) argue that regional divergence of development speeds can explain house price variations. Chodorow-Reich et al. (2024) extend this strand of analyses, demonstrating that long-run city-level fundamentals predict not only 1997–2019 price and rent growth but also the amplitude of the boom–bust–rebound.

Our paper shows that shantytown renovation program affects both housing demand and supply. The program enhances liquidity for shantytown residents, facilitating their relocation and thereby increasing demand in cities attracting these migrants, while simultaneously increasing supply in cities they depart. Additionally, the program effect of replacing each shanty with multiple housing units directly expands housing supply. These mechanisms collectively contribute to regional variations in house price growth.

Furthermore, our findings parallel established patterns in the U.S. housing market, where house prices in higher-income areas react more sensitively to national trends compared to lower-income regions (Mian and Sufi, 2009; Glaeser et al., 2008; Guren et al., 2021 and Howard and Liebersohn, 2023). This pattern is mirrored in our context, because shantytown renovation programs make higher-income areas receiving immigrants, whereas lower-income areas often see an outflow of emigrants.

The third area of focus concerns the economic impacts of slum upgrading programs and urban revitalization policies, which are similar to China's shantytown renovation program in some aspects. Collins and Shester (2013) analyze the local effects of a federal program promoting slum clearance and urban renewal in the U.S., finding significant impacts on income, property values, and population dynamics. Rossi-Hansberg et al. (2010) find that urban revitalization programs implemented in Richmond, Virginia, between 1999 and 2004 increased land prices in neighborhoods targeted for revitalization by 25 percent annually compared to those in a control neighborhood. Diamond and McQuade (2019) find that the Low Income Housing Tax Credit (LIHTC) program, aimed at revitalizing low-income neighborhoods, increased house prices, lowered crime rates, and attracted racially and income diverse populations. Barnhardt et al. (2017) explore the long-term effects of a housing lottery in an Indian city that allowed winning slum dwellers to relocate to improved housing on the city's periphery, examining its consequences on winners' income, human capital, and social networks. Galiani et al. (2017) assess the impact of slum upgrading programs in El Salvador, Mexico, and Uruguay, showing that better housing conditions significantly enhance overall well-being.

These papers primarily address the local economic outcomes and do not examine the broader effects of slum upgrading and urban revitalization on endogenous migration decisions. By contrast, our paper emphasizes the importance of the network spillover effect through endogenous migrations and thus evaluate the countrywide housing market dynamics that result from such policy interventions.

2 Institutional Details and Data

2.1 Institutional Background

Since the mid-1980s, several cities in China initiated small-scale, localized shantytown renovation projects. But these projects were limited in scope and primarily focused on central urban areas. In 2007, the State Council issued the Several Opinions on Solving the Housing Difficulties of Low-Income Families in Urban Areas (No. 24), which provides guidelines for ministries and local governments to formulate policies addressing the housing needs of low-income urban families. Accordingly, in 2009, the Ministry of Housing and Urban-Rural Development (hereafter MoHURD), together with several other ministries and the Peoples Bank of China, issued Guidelines on Shanty Town Renovation in Cities and State-Owned Mining Regions (No. 295), which emphasizes the importance of shanty town renovation in addressing the housing difficulties of middle- and low-income urban residents, improving public facilities and increasing the efficiency of land use.

The shantytown renovation program became a key part of the central government policy agenda since 2013, when Premier Li Keqiang took office. At his first press conference, he pledged that his administration would renovate over 10 million units of various types of shantytowns. In August 2013, the State Council issued Opinions on Accelerating Renovations of Shanty Towns (No. 25), which called for increased financial support from the central and provincial governments and enhanced credit support from banks and other financial institutions for shantytown renovation projects. In June 2014, the China Development Bank, the largest policy bank in China, established its Housing Finance Division, specifically focusing on supporting shantytown renovations along with the construction of urban infrastructure and related projects.

There have been two major ways of compensation to residents displaced during renovation when China implemented the shantytown renovation program. In-kind-based resettlement, or in-kind resettlement for short, is also known as property exchange; it compensates displaced residents with alternative housing. Cash-based resettlement, or cash resettlement for short, directly offers displaced residents with cash so that they can purchase homes from the housing market by themselves.

The in-kind resettlement used to be the dominant compensation method before 2015. In 2015, several real estate policies led to an unprecedented level of unsold home inventories especially in third- and fourth- tier cities. In 2015, Chinas commercial housing sales totaled 1.28 billion square meters only, while the floor area of home inventories held by home developers soared to 7.36 billion square meters.[7] Facing the pressure to reduce housing supply, Beijing started replacing the in-kind resettlement approach with

[7] See the report from Guotai Junan Securities.

cash compensation, under which the displaced residents would become home buyers in the housing market. From 2014 to 2017, the proportion of cash-based resettlement in shantytown renovations increased steadily. It began at 9% in 2014, rose to 28% in 2015, further climbed to 48.5% in 2016, and peaked at 53.9% in 2017.[8]

This increase in cash-based resettlement is supported by the Peoples Bank of China (PBoC), which initiated the Pledged Supplementary Lending (PSL) facility in 2014. The PBoC provides policy banks (primarily CDB) with a long-term, low interest rate funding source for shantytown renovation programs via PSL. Specifically, policy banks apply loans from the PBoC by pledging high-grade bond assets and other collaterals. These funds are then extended to local government financial vehicles (LGFVs) for the shantytown renovation projects.[9] Subsequently, LGFVs compensate shantytown residents through cash-based resettlement, profiting afterward by demolishing and selling the land. When the CDB loans mature, LGFVs pay the loan proceeds back to CDB, who in turn repays the PBoC. From 2014 to 2018, the PBoC injected over 3.5 trillion RMB via PSL. The loans are substantial for CDB. The total liabilities of CDB at the end of 2018 was 14.88 trillion RMB, and the total scale of PSL accounted for 22.7% of the total liabilities.[10]

With the implementation of cash compensation, real estate prices increased significantly and the nationwide level of home inventories decreased over time. By mid-2018, the central government started to lower the cash-based resettlement rate. Since 2019, the central government has tightened its policy on shanty town renovation projects, and subsidized funding have been significantly reduced.

[8]See the news article from People's Daily.

[9]In China, LGFVs are state-owned enterprises that support infrastructure investment at both the provincial and the city level. Since the"four-trillion stimulus plan" which was China's response to the 2007-09 global financial crisis, LGFVs have been one of the major players in the real estate market in China (Bai et al., 2016; Chen et al., 2020).

[10]Not all PSL loans were issued to CDB, as the Agricultural Development Bank of China (ADBC) and the Export-Import Bank of China also became eligible for PSL starting in October 2015. ADBC primarily utilized PSL loans for water conservancy projects and had a small fraction allocated to shantytown renovation, while the Export-Import Bank of China was not involved in shantytown renovation programs and mainly used the funds to promote RMB internationalization by providing RMB loans to oversea projects.

2.2 Data

This section describes the three data sets used in our paper: i) shantytown renovation loan data from CDB; ii) National Population Census data from the National Bureau of Statistics (NBS); iii) housing market data from various sources.

Shantytown renovation loan data. The primary funding for residents' resettlement in shantytown renovation projects comes from policy banks, mostly notably from CDB.[11] In total, there are 38,051 loans issued by CDB for shantytown renovation projects from 2005 to 2022.

Before 2014, CDB imposed a limit of 40% on the share of loans that can be used for cash-based resettlement in the shantytown renovation projects. On March 25, 2015, to support the increased use of cash-based resettlement, the CDB issued a notice titled "Further Improving the Cash-based Resettlement Method in Shantytown Renovation Projects," which removed the 40% cap. After 2018, as the central government tightened its policy on shantytown renovation projects, the issuance of these loans became more stringent.

Figure 2 plots the distribution of CDB loans granted to finance the shantytown renovation program. The contract signing dates of these loans concentrate in the period of 2014-2018, which accounts for 91.89% of all shantytown renovation loans and 85.07% of the total loan amount.[12] We will focus on the period of 2014-2018[13] and aggregate the actual withdrawal amount of all loans signed during 2014-2018 to the city level as the measure of the total size of cash-based resettlement.[14]

[11] Another policy bank, the Agricultural Development Bank of China, also provided some credit support. According to the report from China Securities, CDB accounts for more than 80% of all shantytown renovation loans from policy banks.

[12] Loans granted out of the period of 2014-2018 are also used to finance shantytown renovation projects, but primarily not for the purpose of cash-based resettlement.

[13] As previously discussed, the policy replacing in-kind resettlement with cash-based resettlement was introduced in 2015. However, due to a time lag between contract signing and fund disbursement, many loans contracted in 2014 had their funds released in 2015. Additionally, in-kind resettlement projects were permitted to transition to cash-based resettlement. See a policy example from Hunan province. Furthermore, 2014 marked the first year of accelerated shantytown renovation programs, resulting in a significant number of loan contracts being signed that year. Consequently, we utilize data from 2014 to 2018.

[14] Among these loans, 11% (4,132/34,966) were designated as for provincial-level shantytown projects,

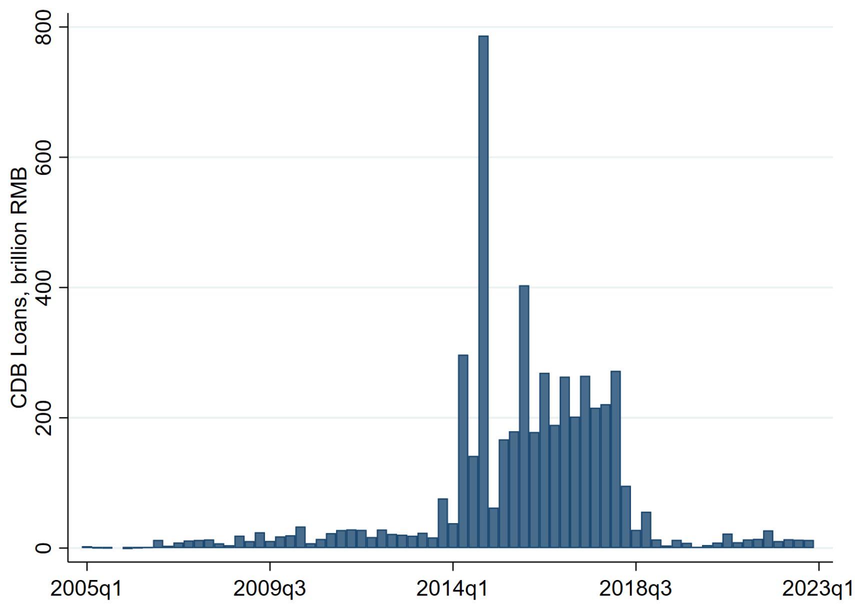


Figure 2: Quarterly Amount of CDB Loans Granted

Note: This figure plots the amount of CDB shantytown renovation loans granted in each quarter.

The scale of loans issued for shantytown renovation in our data is substantial and has had a significant impact on China's housing market. From 2014 to 2018, the China Development Bank (CDB) issued 4.33 trillion RMB in loans for shantytown renovation. Considering a leverage ratio of 2.5 (as implied by the model in Section 4), shantytown renovation increased household mortgages by 6.5 trillion RMB during this period. To contextualize this scale, the outstanding balance of household mortgage in China was 2.98 trillion RMB at the end of 2008, 9 trillion RMB at the end of 2013, and 25.8 trillion RMB at the end of 2018. Thus, the rate of increase in household mortgages accelerated significantly from 2014 to 2018, and shantytown renovation programs contributed approximately 38.7% of the total increase in household mortgages during this period.

National Population Census data. To measure household migration, we utilize a representative sample of the National 1% Population Survey Data of 2015 as well as a rep-

for which we cannot identify the specific city of renovation projects. These loans are excluded from our analysis.

Table 1: Data Summary

	Mean	Median	St. Dev.	Obs
P, RMB/m^2	6991.478	5335.000	6284.377	4613
q	1.930	1.518	1.730	3867
$inv2area$	3.254	1.502	6.705	4555
loan_orig	0.925	0.669	0.970	264
loan_dest	0.058	0.042	0.051	264
demolish	3.379	1.903	9.032	276
Loan2NP	3.678	2.848	3.199	6686
price2rent	32.497	30.000	9.688	4519
buyintent	0.127	0.000	0.333	99291
fore2sale	0.010	0.007	0.013	280

Note: This table reports summary statistics of our data. See Table A.1 for variable definition.

resentative sample of the National Population Census of 2020 from the National Bureau of Statistics. The 2015 survey sample covers 2 million individuals with 217,807 urban households, and the 2020 census sample covers 1.39 million individuals with 487,998 urban and rural households. For each household, we observe their county-level residence and county-level hukou registration at the time of the survey, the type of their hukou (urban or rural), etc. By comparing their residence city with their hukou city, we can identify across-city migration. We focus on urban households, given that shantytown renovation projects mostly engage with households in shanty urban areas.

Housing market data. We combine data from several sources to depict the dynamics of the local real estate markets in China. First, we obtain the city-year level ask prices and price-to-rent ratio of second-hand homes from CityRE, a leading data provider for the Real Estate Sector in China (Deng et al., 2022). The sample covers all the cities in China from 2009-2023. Second, we get the home foreclosure data from the China Index Academy. China Index Academy collects data about all the home foreclosure auctions conducted via various online platforms. This data allows us to compute changes in foreclosure prices and the volume of foreclosed properties in recent years. Third, we collect all the land sale data from landchina.com, which is the official website used by the government to disclose all the land sale information (He et al., 2022). We can observe the location, floor area, price, use type, and transaction method of each land transaction. We focus on the residential land sold through auctions, tender and listing and aggregate the individual sales to the city-year level. Lastly, we get the total transaction area and value of all new home sales at the city level from the Wind database. We use either the area or the value as the measure of housing market size in this paper.

Table 1 reports statistics for key variables used in this paper and Table A.1 in the appendix provides definition for these variables.

3 Empirical Facts

3.1 Econometric Framework

We start with defining the housing market outcome variables and the size of cash-based resettlement at both the originating and the destination cities. For the housing market outcomes, we consider both housing prices and the supply of residential land. As the cash-based resettlement starts in 2015, we will use the year of 2014 as the base year and scale every variable using either the price or the quantity of home sales in 2014. In the following notations, t denotes the year; $o, d, i \in \mathbf{N}$ denote the city, with o denoting migrants' originating cities, d denoting migrants' destination cities, and i denoting generic cities.

For the housing prices, we first calculate $P_{i,t}$, the annual city-level average prices based on the price quotes of all second-hand homes posted in that year.[15] We then scale the housing price by the value in 2014:

$$p_{i,t} \equiv \frac{P_{i,t}}{P_{i,14}}. \tag{1}$$

For the residential land supply, we aggregate all the residential land parcels sold by

[15]The average prices are not quality-adjusted now. We are obtaining more granular data to construct a quality-adjusted price index.

the local government through auctions, tender and listing in each year to get the total floor area of all residential land supply at the city-year level.[16] Denote it by $Q^l_{i,t}$; we then scale it by the size of new home sales in 2014 denoted by $Q^h_{i,14}$:

$$q_{i,t} = \frac{Q^l_{i,t}}{Q^h_{i,14}}.$$

Throughout, h stands for "housing" and l stands for "land."

Lastly, to measure the extent of supply overhang, we estimate the house as well as residential land inventories held by home developers at the city-year level. To do so, we first estimate the annual house inventories at the provincial level in 2007 using the difference between the accumulated floor area of residential land supply and the accumulated house sale area since 1999. We then allocate the provincial-level estimated house inventories and residential land inventories (reported by the NBS) at the beginning of 2007 to different cities proportional to their residential land supply in 2007. Next, starting from 2007, we calculate the house and land inventories for each following year based on the annual flow of house sale and land supply. The year of 2007 is chosen in this procedure because the city-level residential land supply data is available since 2007. Finally, we scale $Inv_{i,t}$, the amount of housing and land inventories in city i at the beginning of year t, by $Q^h_{i,14}$:

$$inv2area_{i,t} = \frac{Inv_{i,t}}{Q^h_{i,14}}.$$

We measure the size of cash-based resettlement using the withdrawal amount of CDB shantytown renovation loans granted during 2014-2018. In the originating cities, we aggregate all the individual CDB loans of which the loan contracts were signed during 2014-2018 to finance projects in that city. Denote it as $Loan_i$ for city i. We then scale it by the total home sales in that city in 2014:

$$loan\_orig_i = \frac{Loan_i}{Sale_{i,14}}.$$

[16]We exclude an allocation mechanism called "bilateral agreement", which is typically used when the residential land is used to built affordable houses or to accommodate displaced households due to land requisition.

Our paper highlights the economic significance of intercity money flow of the CDB loans. Denote the total number of urban households from the originating city o by N_o, among which $M_{o,d}$ live and work in city d by 2015. Money flow can occur through both the existing migration network and additional new household migration since 2015. Regardless of which channel, we assume the total amount of money flow from city o to i is proportional to $Loan_o \cdot \frac{M_{o,d}}{N_o}$. We then aggregate $Loan_o \cdot \frac{M_{o,d}}{N_o}$ across originating cities o and proxy the size of cash compensation at the destination city d as follows:

$$Loan\_Dest_d = \sum_{o \neq d} Loan_o \cdot \frac{M_{o,d}}{N_o}$$

Similarly, we scale the $Loan\_Dest_d$ by the size of the housing market in 2014:

$$loan\_dest_d = \frac{Loan\_Dest_d}{Sale_{d,14}}$$

We stress that $loan\_dest_d$, which only factor in the migration network that existed in 2015, only proxies for the relative size of cash-based resettlement across destination cities after 2015. It is not the actual CDB loans that have flowed into the destination city after 2015, nor an unbiased estimator of this economic variable. An important factor that affect the total migration after 2015 is the endogenous changes of the migration network after 2015, presumably due to changes in the spatial distribution of housing prices. This plays an important role in our structural model.

Table 1 reports the summary statistics. The size of cash-based resettlement at the originating cities is about 92.9% of the total transaction value of the housing market in 2014. The flow to the destination cities as captured by *loan_dest*, is about 5.8% of the total transaction value of the housing market in 2014. But note that *loan_dest* is not an unbiased estimator of the actual money flow.

In the following sections, we will first document how the size of cash-based resettlement measured by *loan_orig* and *loan_dest* affects the housing price and supply, and then give direct evidence on the mechanism, i.e., money flow through existing network by 2015 as well as additional migration after 2015. Finally, we will provide suggestive evidence on the existence of housing speculation triggered by the cash-based resettlement.

3.2 Housing Market Responses

The policy impact on price. To study the impact of the cash-based resettlement on local housing prices, we use the following event study specification:

$$p_{i,t} = \sum_{\tau \neq 2014} \beta_\tau \cdot \mathbf{1}_{t=\tau} \cdot loan\_orig_i + \gamma_\tau \cdot \mathbf{1}_{t=\tau} \cdot loan\_dest_i + \delta_i + \theta_{p(i),t} + \epsilon_{i,t} \tag{2}$$

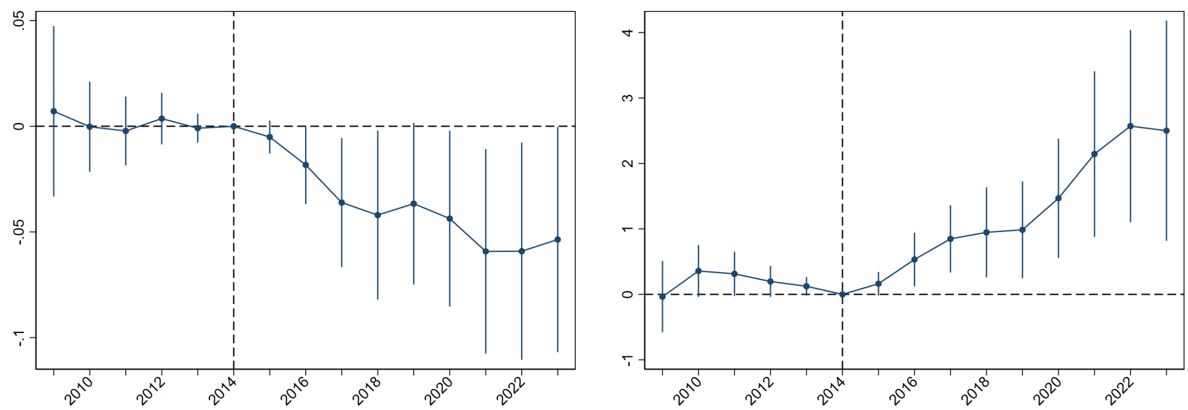
The year of 2014 is taken as the base year. The coefficients $\{\beta_\tau\}$ and $\{\gamma_\tau\}$ capture the growth of local housing prices relative to the year of 2014 in response to the exposure to cash-based resettlement. We include the city fixed effect δ_i to control for time-invariant city characteristics and the province-by-year fixed effect $\theta_{p(i),t}$ to control for any provincial-level shocks (with $p(i)$ denoting the province where city i is located).

To interpret the coefficients, recall from Eq. (1) we have

$$p_{i,t} = \frac{P_{i,t}}{P_{i,14}} = \frac{P_{i,t} \cdot Q^h_{i,14}}{Sale_{i,14}}. \tag{3}$$

Therefore the coefficient, β_τ, tells us that if the quantity transacted is fixed, for every one RMB of CDB loan at the originating city, how much the total transaction value of homes will change in year τ. The interpretation of the coefficient γ_τ is different as *loan_dest* is not an unbiased estimator for the money inflow through networks. For example, if on average the actual money flow is twice of *loan_dest*, then for every one RMB of CDB loan at the destination cities the total housing transaction value should increase by $\frac{\gamma_\tau}{2}$ in year τ.

Figure 3 shows the estimation results. Before 2014, there is no significant difference in housing price growth across cities with different *loan_orig* or *loan_dest*, as both $\hat{\beta}_\tau$ and $\hat{\gamma}_\tau$ are insignificant and close to zero. After 2014, $\hat{\beta}_\tau$ becomes significantly negative, with its magnitude growing over time from almost 0 in 2015 to -0.054 in 2023. The coefficient $\hat{\gamma}_\tau$, in contrast, becomes significantly positive for $\tau > 2014$ and increases from 0.16 in 2015 to 2.50 in 2023. We interpret the negative effect of *loan_orig* as due to a net increase



(a) Originating Cities (*loan_orig*) (b) Destination Cities (*loan_dest*)

Figure 3: Responses of Housing Prices to the Cash-based Resettlement

Note: This figure plots the 95% confidence interval of the effect of *loan_orig* and *loan_dest* on the average ask price of second-hand homes normalized to be one in 2014. Standard errors are clustered by cities.

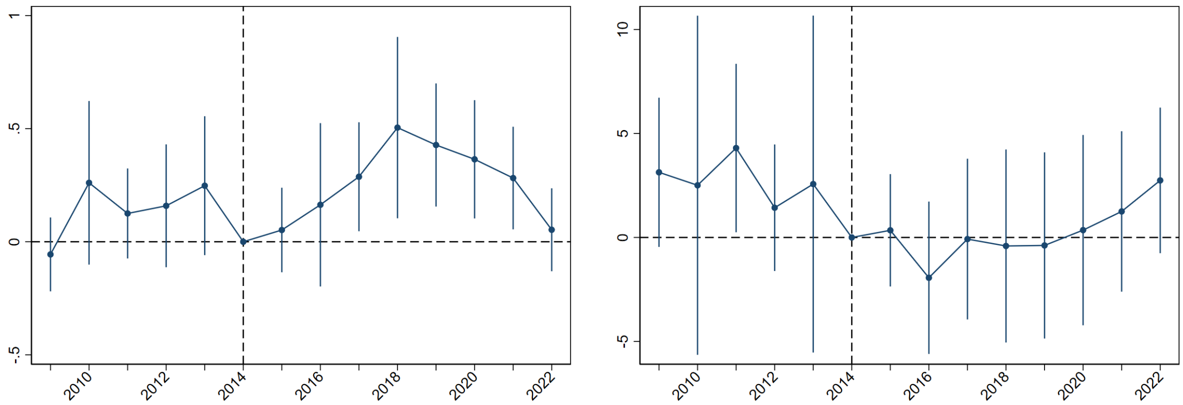
of housing supply (which will be shown below) together with an outflow of demand due to accelerated emigration. The positive effect of *Loan_dest* is consistent with higher demand due to more money inflow.

Without taking into account the general equilibrium effect, consider the counterfactual scenario in which the shantytown renovation with cash-based resettlement is absent. The increase of $loan\_dest_i$ from 0 to its mean predicts the housing price growth by 14.5%, while the the increase of $loan\_orig_i$ from 0 to its mean predicts the housing price drop by 5.0%.

The policy impact on quantity. To study the impact on the residential land supply, we consider new residential land supply with the same specification as for housing prices:

$$q_{i,t} = \sum_{\tau \neq 2014} \beta_\tau \cdot \mathbf{1}_{t=\tau} \cdot loan\_orig_i + \gamma_\tau \cdot \mathbf{1}_{t=\tau} \cdot loan\_dest_i + \delta_i + \theta_{p(i),t} + \epsilon_{i,t} \tag{4}$$

Figure 4 reports the estimation results. Although insignificant, cities with higher *loan_orig* appear to have had more residential land supply relative to $Q^h_{i,14}$ before 2014,



(a) Originating Cities (*loan_orig*)

(b) Destination Cities (*loan_dest*)

Figure 4: Responses of Residential Land Supply to the Cash-based Resettlement

Note: This figure plots the 95% confidence interval of the effect of *loan_orig* and *loan_dest* on the residential land supply scaled by the housing market transacted area in 2014. Standard errors are clustered by cities.

which may be related to why these cities conducted a larger scale of cash-based resettlement. After 2014, $\hat{\beta}_\tau$ are also positive, and turn significantly positive around 2017, with the magnitude peaking around 0.5 in 2018 and gradually decreases to almost zero in 2022. The cumulative effect for 2015-2022 is approximately 2.13. This is likely because the shantytown renovation program allows the government to acquire from households a significant amount of underdeveloped land, which can later be supplied to the market.

Of course, any shantytown renovation program starts with demolishing some existing dwellings. To examine whether *loan_orig* has led to a net increase or decrease in residential land supply, we check the size of shanty homes demolished due to the cash-based resettlement. Specifically, denote by $DemolishArea_i$ the total floor area of shanty homes demolished under all projects financed by CDB loans which we use to construct *loan_orig*, and define

$$demolish_i = \frac{DemolishArea_i}{Q^h_{i,14}}$$

We then run the cross-sectional regression of $demolish_i$ on $loan\_orig_i$:

$$demolish_i = k \cdot loan\_orig_i + \theta_{p(i)} + \epsilon_i$$

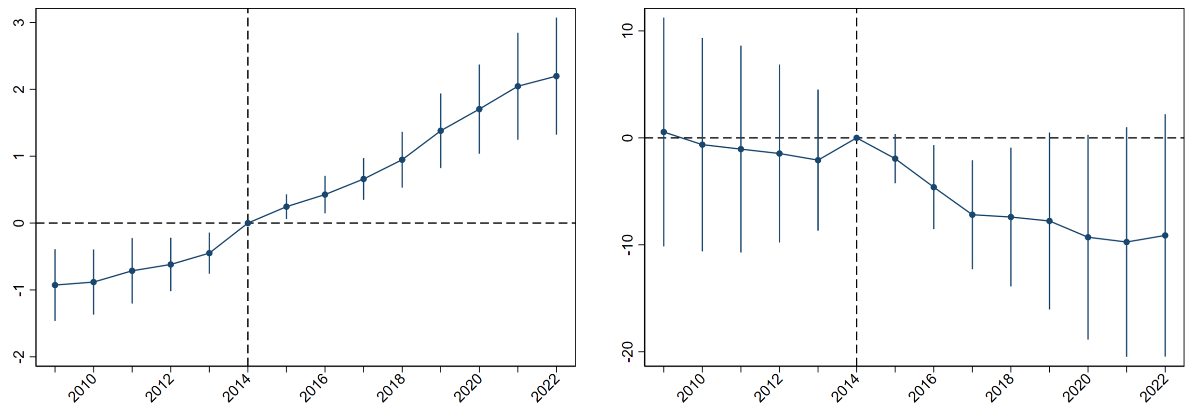
Table A.2 in the Appendix estimates $\hat{k}$ to be 1.59. By comparing $\hat{k}$ with $\sum_{\tau>2014} \hat{\beta}_\tau$, we conclude that the program leads to more new residential land supply than demolished and hence a net increase of residential housing supply, which is consistent with the negative effect of *loan_orig* on the housing prices. The net supply increase likely because of the increase of plot ratio, i.e., the new residential buildings are taller and have more stories than previous-constructed buildings and hence the same size of land can offer more floor area of homes.

The other coefficient, γ_τ, in contract, is mostly insignificant (except in 2022). This suggests that although housing demand by migrants has pushed up local housing price, local governments did not respond by increasing housing supply.

Supply Overhang. Based on the facts documented above, cash-based resettlement had important implications on the spatial variation in housing supply relative to demand. In the originating cities, the net increase of residential land supply and the decreased local housing demand due to emigration suggest that these cities would end up with even more severe supply overhang after the program. In contract, in destination cities, the increase of housing demand along with an unresponsive residential land supply suggests that they will end up with less supply overhang. To test these predictions, we examine land and home inventories with the same specification as before:

$$inv2area_{i,t} = \sum_{\tau \neq 2014} \beta_\tau \cdot \mathbf{1}_{t=\tau} \cdot loan\_orig_i + \gamma_\tau \cdot \mathbf{1}_{t=\tau} \cdot loan\_dest_i + \delta_i + \theta_{p(i),t} + \epsilon_{i,t} \quad (5)$$

Figure 5 reports the estimation results. First, as we conjectured and contrary to the authority's claims, cities that adopted larger-scale cash-based resettlement did not experience a reverse or slowdown of the increase of inventories. In fact, the total size of land and home inventories held by home developers kept increasing at a similar speed as before.



(a) Originating Cities (*loan_orig*) (b) Destination Cities (*loan_dest*)

Figure 5: Responses of Inventories to the Cash-based Resettlement

Note: This figure plots the 95% confidence interval of the effect of *loan_orig* and *loan_dest* on the city's land and home inventories held by home developers scaled by the housing market transacted area in 2014. Standard errors are clustered by cities.

Second, while exhibiting parallel path before 2014, destination cities with more money inflow experienced a larger drop in inventories after 2014. Using the estimated coefficient in 2022, the increase of *loan_dest* from 0 to its mean is associated with an increase of *inv*2*area* by 0.53 in 2022. This is economically significant as the average of *inv*2*area* in 2022 is about 4.26.

3.3 Money Flow and Household Migration

At the core of our paper is the reallocation of money through the migration network. The reallocation can occur not only through the existing migration network but also by encouraging additional household migration. In this section we provide evidence supporting both channels.

Money Flow through Existing Network. Standing at 2015, individuals who came from city o and are living in other cities can still benefit from cash-based resettlement in city o because either they or their parents own residential properties there. Based the probability of receiving cash compensation is independent of residence location, on average these migrants would receive cash compensation of $\frac{Loan_o}{N_o}$ per household, who can use these proceeds to purchase houses in their destination cities (where they are living). This is an important channel through which cash-based resettlement money funded by CDB loans granted to originating cities eventually flows to destinations cities.

To test this hypothesis, we calculate the size of houses that the migrant households can purchase at the destination city with the cash compensation of $\frac{Loan_o}{N_o}$:

$$Loan2NP_{o,d} = \frac{Loan_o}{N_o} \cdot \frac{1}{P_{d,14}},$$

and then check whether $Loan2NP_{o,d}$ affects the residence and home ownership in 2020 of migrant households that moved before 2015. Specifically, we conduct the following cross-sectional regression analysis:

$$y_{o,d} = \beta \cdot Loan2NP_{o,d} + \delta_d + \epsilon_{o,d},$$

Here, the outcome variable $y_{o,d}$ can be home purchase decisions of those who moved from city o to city d before 2015. We control for the destination city fixed effect to absorb any city-level factors that may affect the immigrants' stay and home-purchasing decisions, such as hukou restrictions.

Because immigrants who migrated long ago likely have already owned homes by 2015 and therefore unlikely to adjust their residence cities, we focus on those that migrated during 2011-2015. We consider two dependent variables: the percentage of these migrants that remain in the destination city d at the end of 2020, and the percentage of local home owners at the end of 2020.

Table 2 reports the results. In Column (1), $Loan2NP$ has a significant and positive effect on the fraction of 2015 migrants that remained in the destination cities in 2020. A one standard deviation increase in $Loan2NP$ would predict 10.2% more urban migrants that remained in 2020. In Column (2) we focus on those who not only remain but also own homes in the destination cities in 2020. Based on the coefficient estimates, a one standard deviation increase in $Loan2NP$ would predict 9.2% more home owners in 2020. Almost all the effect on those that remain comes from the fact that they become local

Table 2: Money Flow Through Existing Migrants

	(1)	(2)	(3)
Dep Var:	stay in 2020	homeowner in 2020	homeowner in 2015
Loan2NP	0.0319**	0.0287**	-0.00506**
	(2.55)	(2.42)	(-2.47)
Destination City FE	Yes	Yes	Yes
Pseudo-R2	0.094	0.077	0.294
Obs	4855	4855	4855

Note: This table shows conditional on those urban households that have migrated to other cities during 2011-2015, how the size of the cash-based resettlement in their originating cities affects the fraction that remain at the destination cities (Column (1)), the fraction of local homeowners (Column (2)) in 2020, and whether there is any correlation with their home ownership in 2015 (Column (3)).

home owners.

In Column (3), we use the fraction of these 2015 migrants as home owners in 2015 as the dependent variable. Although the magnitude is small, there exists a significant and negative correlation between $Loan2NP$ and home ownership in 2015. This result is likely due to the fact that the size of cash-based resettlement is negatively correlated with the urban average wages at the originating cities. Lower wages in the originating cities negatively impacted those migrants from buying new homes. This negative correlation suggests that the coefficient estimates in Column (1) and (2) are a lower bound of the true effect of $Loan2NP$.

Household Migration. The cash-based resettlement could also boost intercity migration. As their homes are acquired by the local government, households have to search for a new home. Some of them may choose to migrate to a different city, especially those who prefer to migrate but did not; they initially could not sell their homes (given the secondary housing market friction) to finance the purchase of a new home in another city, but now can thanks to the cash-based resettlement program.

To test this prediction, we consider the treatment effect of cash-based resettlement on the city's household emigration using the Difference-in-difference (DID) strategy. For the

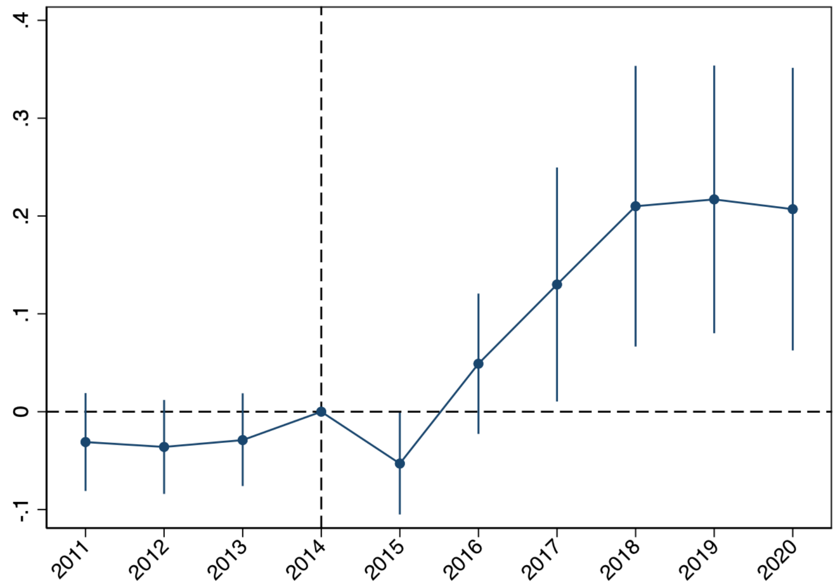


Figure 6: Cash-based Resettlement and Intercity Migration

Note: This figure plots the 95% confidence interval of the effect of $\frac{LocalRecipient}{N}$ on the city's urban household intercity emigration. Standard errors are clustered by cities.

outcome variable, we calculate $m_{o,d}$, the total number of urban households that emigrate from city o in year t, and scale it by N_o, the number of urban households originating from city o.

For the treatment variable, we calculate the number of urban households who received the cash compensation and still lived in the originating city o by 2015 (and hence are available for migration):

$$LocalRecipient_o = \frac{Loan_o}{\bar{H}_o P_{o,14}} \times (1 - \frac{\sum_i M_{o,d}}{N_o}), \tag{6}$$

and scale it by N_o. Conceptually, the effect of cash-based resettlement on household emigration depends on how many households out of $LoanRecipient_o$ choose to migrate.

We then conduct the DID analysis using the following specification:

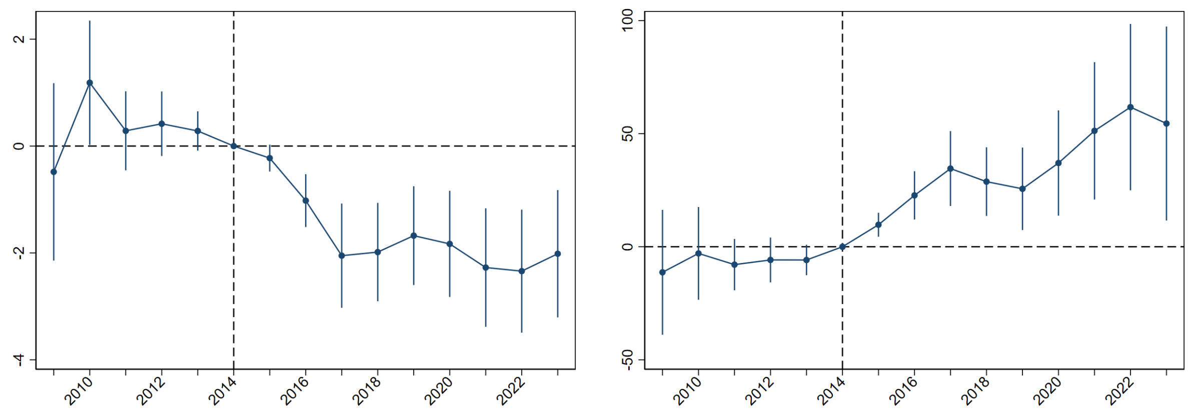
$$\frac{m_{o,t}}{N_o} = \sum_{\tau \neq 2014} \beta_\tau \cdot \mathbf{1}_{t=\tau} \cdot \frac{LocalRecipient_o}{N_o} + \delta_d + \theta_{p(d),t} + \epsilon_{d,t}$$

Figure 6 plots the estimated coefficients $\{\hat{\beta}_\tau\}$ over time with their 95% confidence intervals. The resulting coefficients are both insignificant and close to zero before 2014, supporting the parallel trend assumption between treated and controls. After 2014, we find a significant and positive treatment effect, suggesting that cities with more households receiving the cash compensation experience more household migration.

3.4 Housing Speculation

Housing markets are widely recognized as subject to speculation, especially in China. Households may purchase homes not for residence but for investment purposes, i.e., they expect the housing prices to go up. As people usually form expectation by extrapolation, the large-scale housing price movements induced by the cash-based resettlement of the shantytown renovation program could stimulate local speculation. We present three pieces of evidence on the speculation of home buyers that are triggered by the program since 2015.

Price-to-rent ratio. The first piece of evidence is related to the home price-to-rent ratio. A higher price-to-rent ratio signals more optimistic expectations of future housing price growth. Using the same DID estimation specification as Eq. (2), we find a persistent and positive effect of *loan_dest* on the local home price-to-rent ratio, as well as a persistent and negative effect of *loan_orig* on the local home price-to-rent ratio as shown in Figure 7. As the cash-based resettlement depresses housing prices in the originating cities and increases housing prices in the destination cities, households may expect the price change to continue. As a result, the local home price-to-rent ratio went down while the price-to-rent ratio in destination cities with money and household inflow went up.



(a) Originating Cities (*loan_orig*)   (b) Destination Cities (*loan_dest*)

Figure 7: Responses of Home Price-to-Rent Ratio to the Cash-based Resettlement

Note: This figure plots the 95% confidence interval of the effect of *loan_orig* and *loan_dest* on the city's average price-to-rent ratio. Standard errors are clustered by cities.

Local household intention to buy homes. The second piece of evidence is on local household intention to buy homes. In cities that experienced an increase in housing prices, the local non-home-owners are adversely impacted. Without speculation, their housing demand should decrease. With speculation, they may increase housing demand if they expect the price increasing trend to continue. Similarly, in cities that experienced a decrease in housing prices due to the shantytown renovation program, the local non-home-owners are positively affected. Without speculation, their housing demand should have increased, even if they do not receive the cash compensation. With speculation, however, their demand may decrease if they expect the price decreasing trend to continue.

To test these predictions, we use data from the China Household Financial Survey. We focus on the households with hukou in their residence cities who are not home-owners by excluding those that ever made any home purchases since 2000.[17] We then examine whether and how their intention to buy homes in the future is related to *loan_dest* and

[17] Table A.3 in Appendix reports results when we include all households with hukou in residence cities, regardless of their home purchase history since 2000. The coefficient estimates barely change.

Table 3: Local Household Intention of Buy Homes

Dep Var: buyintent	(1)	(2)	(3)	(4)
Year	2013	2015	2017	2019
loan_orig	-0.000849	-0.0218***	-0.0131***	-0.00908**
	(-0.0868)	(-3.434)	(-2.685)	(-2.228)
loan_dest	0.0275	0.302**	0.517***	0.224**
	(0.146)	(2.189)	(3.874)	(2.273)
Prov FE	Yes	Yes	Yes	Yes
Observations	13,695	11,831	15,650	18,762
R-squared	0.012	0.008	0.009	0.007
#Cities	140	145	146	138

Note: This table reports the effect of *loan_orig* and *loan_dest* on the local household intention to buy homes in the future. The sample is from the China Household Finance Survey and only includes households with hukou in their residence cities who have not made any home purchases since 2000. Standard errors are clustered by city. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

loan_orig. Specifically, we run the following regression for each survey year:

$$buyintent_{i,k,t} = \beta_t \cdot loan\_orig_i + \gamma_t \cdot loan\_dest_i + \theta_{p(i),t} + \epsilon_{i,k,t}. \tag{7}$$

In Eq. (7), i denotes the city, k the household, and t the year.

Table 3 reports the results. In Column (1), both estimates of β and γ are insignificant. This serves as a placebo test showing that without the cash-based resettlement, there is no significant correlation between our explanatory variables and the household home-purchasing intention. Column (2)-(4) show that the coefficient estimates of *loan_orig* are significantly negative while the coefficient estimates of *loan_dest* are significantly positive, consistent with the speculation hypothesis as we discuss above.

Foreclosure. The last piece of evidence is based on mortgage foreclosure. We test whether more home purchase by local households due to speculation rather than an increase in their income has led to more mortgage foreclosure. The foreclosure price

Table 4: Home Foreclosure and the Shantytown Renovation Program

	(1)	(2)
Dep Var	foreclosure price growth	fore2sale
loan_orig	0.0393***	-0.001
	(3.355)	(-0.423)
loan_dest	-0.299	0.087**
	(-1.483)	(2.129)
Prov FE	Yes	Yes
Observations	251	258
R-squared	0.226	0.428

Note: This table reports the correlation between the size of cash-based resettlement at originating (*loan_orig*) and destination cities (*loan_dest*) with the change of home foreclosure prices from 2021 to 2022, and the total foreclosure home size during 2022-23 relative to the accumulate new home sale size during 2015-2021. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

data is also interesting in the sense that the foreclosure prices are determined only by the buyers who participate in the foreclosure auction, and can therefore reveal the buyer's beliefs, while the housing prices that we use so far are the ask prices quoted by the sellers.

We examine the foreclose data since 2021, when the national average housing price growth turns negative. We calculate the price growth from 2021 to 2022 and run the following cross-sectional regression:

$$\Delta(\ln foreclosureprice)_i = \beta \cdot loan\_orig_i + \gamma \cdot loan\_dest_i + \theta_{p(i)} + \epsilon_i, \tag{8}$$

Here, $\Delta(\ln foreclosureprice)_i$ is the growth of foreclosure transaction prices from 2021 to 2022. Column (1) in Table 4 shows that in cities with higher *loan_orig* or lower *loan_dest*, the foreclosure prices experienced a smaller drop since 2021, suggesting a reversal of the previous trend.

In Column (2) of Table 4 we consider the size of mortgage foreclosure. The speculators are more likely to default on mortgages as their home purchases are driven by future belief instead of their income. We calculate the rate of home foreclosure by scaling the total size of homes with mortgage foreclosure in 2022-23 by the accumulated home sale size during 2015-2021, and use it as the dependent variable in the above cross-sectional regression. Consistent with our conjecture, the coefficient of γ is significant and positive. One standard deviation increase of *loan_dest* will increase the foreclosure rate by 0.44%, which is considerable large compared to the mean of 3.15%.

To conclude, the three pieces of evidence supports the presence of speculation triggered by the cash-based resettlement of the shantytown renovation program. As the case-based resettlement led to large-scale price movements, those that did not receive the cash compensation speculated on the price movements. But in recent years when the housing price growth trend slowed down and reverted, they ended up with a worse condition.

4 Spatial General Equilibrium Model

To quantify the effect of the cash-based resettlement after taking into account endogenous household migration and other general equilibrium forces, this section builds and estimates a standard quantitative spatial model, based on which we conduct quantitative counterfactual analysis in Section 5. In the model, we will allow housing prices and household migration to be jointly determined in equilibrium, and take other variables such as the total size of migrant households and the prevailing wage level in each city as given.

4.1 Setup

Household Migration. Consider an urban household born in or from originating city o that migrates to city d. He will sell his house in city o of size $\bar{H}_o$ at price P_o, and supply one unit of labor and earn wage w_d in city d. He will then allocate his wealth in goods consumption C and local housing H of price P_d. In addition to consuming the housing services, he will also leave the house as a bequest to his offspring and he cares about the welfare of his offspring. Suppose his subjective belief about the housing price at the time of leaving bequest is $g_p \cdot P_d$. Therefore he will solve the following optimization problem, conditional on the originating city o and destination city d:

$$\max_{C,H} \ \ln\left((C^{\alpha} \cdot H^{1-\alpha})^{\gamma} \cdot B^{1-\gamma}\right) \tag{9}$$
$$s.t. \quad C + P_d H = w_d + P_o \bar{H}_o, B = g_p P_d H.$$

In addition, when migrating from city o to city d, there is a reallocation cost $\kappa_{o,d}$ and individual-specific location preference $\nu^n_{o,d}$ where n denotes the individual household. The total indirect utility of the urban household n from migrating from city o to d is:

$$V^{u,n}_{o,d} = \underbrace{\epsilon^u \cdot \Big(\ln\left((\alpha\gamma)^{\alpha\gamma}(1-\alpha\gamma)^{(1-\alpha)\gamma+1-\gamma} g_p^{1-\gamma} \cdot P_d^{-(1-\alpha)\gamma}(w_d + P_o\bar{H}_o)\right) - \phi^u \ln(\kappa_{o,d}) \Big)}_{V^u_{o,d}} + \nu^n_{o,d},$$

where ϵ^u and ϕ^u are the urban household migration elasticities that govern the importance of mean utility relative to the idiosyncratic preference. Throughout we use "u" to indicate "urban" and "r" to indicate "rural." We assume that $\nu^n_{o,d}$ is drawn from the standard Gumbel distribution. Integrating across household n, the share of urban households from originating city o who wish to migrate to city d (if they can) is:

$$\lambda_{u,o,d} = \frac{\left(\frac{w_d + P_o\bar{H}_o}{P_d^{(1-\alpha)\gamma}}\right)^{\epsilon^u} \kappa_{o,d}^{-\epsilon^u\phi^u}}{\sum_i \left(\frac{w_i + P_o\bar{H}_o}{P_i^{(1-\alpha)\gamma}}\right)^{\epsilon^u} \kappa_{o,i}^{-\epsilon^u\phi^u}}, \tag{10}$$

We assume that only those that can sell their homes in the originating cities can migrate; this can be justified with financial constraints given limited personal wealth. Denote the probability that the household can sell their houses as η_o. The share of migration is then given by follows:

$$\mu_{u,o,d} = \begin{cases} \eta_o \cdot \lambda_{u,o,d} & \text{if } o \neq d, \\ 1 - \eta_o + \eta_o \cdot \lambda_{u,o,o} & \text{if } o = d. \end{cases} \tag{11}$$

More broadly, the parameter $1 - \eta_o$ can be thought of as a reduced-form parameter that captures all types of migration frictions that keeps households in their originating cities. For instance, these frictions in the context of China include hukou restrictions as well as various eligibility requirement on who are qualified to buy local homes.

Similar to the urban households, rural households from originating city o also need to decide which city to work and live in. Unlike urban households, rural households cannot sell their houses in the rural area, and hence their wealth only consists of wage w_d at the destination city. Moreover, due to frictions such as concerns for land security if they migrate to different cities, we assume only ξ_o fraction of rural households will make the migration decisions (that is to say, the remaining $1-\xi_o$ will move to the urban area of city o so that they can frequently check their rural land).

Similarly, for rural households that are willing or able to migrate, we have

$$\lambda_{r,o,d} = \frac{\left(\frac{w_d}{P_d^{(1-\alpha)\gamma}}\right)^{\epsilon^r} \kappa_{o,d}^{-\epsilon^r \phi^r}}{\sum_i \left(\frac{w_i}{P_i^{(1-\alpha)\gamma}}\right)^{\epsilon^{u^r}} \kappa_{o,i}^{-\epsilon^r \phi^r}}; \tag{12}$$

Here, "r" indicates "rural" households. Therefore the share of rural households from originating city o who migrate to city d is

$$\mu_{r,o,d} = \begin{cases} \xi_o \cdot \lambda_{r,o,d} & \text{if } o \neq d \\ 1 - \xi_o + \xi_o \cdot \lambda_{r,o,o} & \text{if } o = d \end{cases} \tag{13}$$

Housing Speculation. To capture the investment feature of homes, we introduce housing speculators to the model. Denote the amount of capital from speculators in city d as K_d and the total one-period opportunity cost of capital as $F(K_d) = \frac{1}{a} \cdot \frac{K_d^2}{N_d w_d} + K_d R$, where a is a constant, N_d is the number of local urban households in city d, and R is the return of alternative assets.

We assume the speculators are rational and form correct belief about the future housing price growth. As a result of this assumption, speculators will move housing supply across different periods and smooth housing price growth. Denote their anticipated one-period house price growth as $\hat{P}^e_d$. Since there is no uncertainty, we have

$$F'(K_d) \geq \hat{P}^e_d \text{ with equality if } K_d > 0 \implies K_d = \frac{\max(\hat{P}^e_d - R, 0) \cdot aN_d w_d}{2}.$$

Housing Market Clearing. Housing supply in the urban area of city d includes two parts. The first is an inelastic supply of new houses, H_d, from home developers. The second is the houses owned by the urban households who are making their residence location decisions, which is $\bar{L}_{u,d}\bar{H}_d$ where $\bar{L}_{u,d}$ is the number of urban households born in city d.

On the side of housing demand, it comes from both the rural and urban households born and staying in city d and those that migrate to city d. Denote the number of rural households born in city d as $\bar{L}_{r,d}$. The optimization problem in (9) above implies that the household will spend $1 - \alpha\gamma$ fraction of their wealth on housing.

Combining these two pieces together, the market clearing condition is:

$$\underbrace{P_d \cdot (H_d + \bar{L}_{u,d}\bar{H}_d)}_{\text{Supply at city } d} = \underbrace{(1 - \alpha\gamma) \times \sum_o \left[\bar{L}_{u,o}\mu_{u,o,d} \cdot (w_d + P_o\bar{H}_o) + \bar{L}_{r,o}\mu_{r,o,d} \cdot w_d\right] + K_d}_{\text{Demand at city } d}. \quad (14)$$

4.2 Shantytown Renovation

We will consider two periods: $t = 1$ corresponds to 2011-2015 when there is no cash-based resettlement, and $t = 2$ corresponds to 2016-2020 with the cash-based resettlement. Assume that if there was no cash-based resettlement in $t = 2$, the total number of urban migrants would be $\bar{L}'_{u,i} = \ell\bar{L}_{u,i}$, the total number of rural migrants would be $\bar{L}'_{r,i} = \bar{L}_{r,i}$, and total new housing supply would be $H'_i = \rho_1 H_i$.

The shantytown renovation program under cash-based resettlement generates shocks to both sides of demand and supply. Denote the total number of urban households who receive the cash compensation as S_o and the fraction of such households as s_o. Denote the fraction of households with local hukou that live in other cities at the beginning of period $t = 2$ as mo_o. The number of cash-recipient households that will make migration decisions at $t = 2$ is $S_o(1 - mo_o)$; this corresponds to *LocalRecipient* defined in (6) in

Section 3.3. The total number of urban households who will make migration decisions is hence

$$\bar{L}'_{u,o} = S_o(1 - mo_o) + \ell \bar{L}_{u,o}(1 - s_o). \tag{15}$$

Among these households given in (15), $S_o(1 - mo_o) + \ell \bar{L}_{u,o}(1 - s_o)\eta_o$ are unlocked from their previous homes and can migrate to other cities, and $\ell \bar{L}_{u,o}(1 - s_o)(1 - \eta_o)$ are tied to their originating city. The share of migration is hence

$$\mu'_{u,o,d} = \begin{cases} \eta'_o \cdot \lambda'_{u,o,d} & \text{if } o \neq d, \\ 1 - \eta'_o + \eta'_o \cdot \lambda'_{u,o,o} & \text{if } o = d, \end{cases} \tag{16}$$

where λ'_u depends on P' as given by Eq. (10), and the new liquidity measure η'_o is the fraction of urban migrants that either sell their homes or have their homes purchased by the government:

$$\eta'_o = \frac{S_o(1 - mo_o) + \ell \bar{L}_{u,o}(1 - s_o)]\eta_o}{\bar{L}'_{u,o}}.$$

On the supply side of the destination city d, with $S_d \bar{H}_d$ homes purchased from the households, the government will built $\nu S_d \bar{H}_d$ homes, where ν captures the adjustment of plot ratios. Therefore the housing market clearing condition at $t = 2$ is:

$$P'_d \cdot (H'_d + \ell \bar{L}_{u,d} \bar{H}_d(1 - s_d) + \frac{K_{r,d}}{P_d}) = (1 - \alpha\gamma) \times \sum_o \left[\bar{L}'_{u,o} \mu'_{u,o,d} \cdot (w'_d + P'_o \bar{H}_o) + \bar{L}_{r,o} \mu'_{r,o,d} \cdot w'_d \right], \tag{17}$$

where $H'_d = \rho_1 H_d + \rho_2 \cdot S_d \bar{H}_d$.

4.3 Solving the Model

We conduct the counterfactual analysis using the standard "exact hat algebra" in the trade literature (Costinot and Rodríguez-Clare, 2014; Dingel and Tintelnot, 2021). Define the relative change of any economic variable x as $\hat{x} = \frac{x'}{x}$.

First, regarding the market clearing condition, the relative changes satisfy:

$$
\begin{aligned}
&\hat{P}_d \cdot \Big(\underbrace{(\rho_1 + \rho_2 \frac{S_d \bar{H}_d}{H_d})}_{\hat{H}_d} \cdot \theta_d + \ell(1 - s_d) \cdot (1 - \theta_d) + \frac{K_{r,d}}{P_d(H_d + \bar{L}_{u,d}\bar{H}_d)}\Big) \\
&= \sum_o \left[\gamma_{u,o,d} \cdot \hat{L}_{u,o} \cdot \hat{\mu}_{u,o,d}(\hat{P}_o \cdot \delta_{o,d} + \hat{w}_d \cdot (1 - \delta_{o,d})) + \gamma_{r,o,d} \cdot \hat{\mu}_{r,o,d}\hat{w}_d\right],
\end{aligned}
\tag{18}
$$

where

$$
\begin{aligned}
\hat{L}_{u,o} &= \ell(1 - s_o) + \frac{S_o(1 - mo_o)}{\bar{L}_{u,o}} \\
\theta_d &= \frac{H_d}{H_d + \bar{L}_{u,d}\bar{H}_d}, \quad \delta_{o,d} = \frac{P_o \bar{H}_o}{w_d + P_o \bar{H}_o}, \\
\gamma_{u,o,d} &= \frac{\bar{L}_{u,o}\mu_{u,o,d} \cdot (w_d + P_o\bar{H}_o)}{\sum_o \left[\bar{L}_{u,o}\mu_{u,o,d} \cdot (w_d + P_o\bar{H}_o) + \bar{L}_{r,o}\mu_{r,o,d} \cdot w_d\right] + \frac{\max(\hat{P^e}_d - R, 0) \cdot aN_d w_d}{2(1-\alpha\gamma)}} \\
\gamma_{r,o,d} &= \frac{\bar{L}_{r,o}\mu_{r,o,d} \cdot w_d}{\sum_o \left[\bar{L}_{u,o}\mu_{u,o,d} \cdot (w_d + P_o\bar{H}_o) + \bar{L}_{r,o}\mu_{r,o,d} \cdot w_d\right] + \frac{\max(\hat{P^e}_d - R, 0) \cdot aN_d w_d}{2(1-\alpha\gamma)}}
\end{aligned}
$$

At $t = 1$, the speculative households did not anticipate the introduction of the cash-based resettlement, and they formed belief about $\hat{P}^e_d$ by assuming $(s_d, S_d) = (0, 0)$ in Equation (18). Therefore, we will solve for $\hat{p}^e$ by setting $(s_d, S_d) = (0, 0)$ and $\hat{p}^e = \hat{p}$. Given the solution of $\hat{p}^e$, we then solve for $\hat{p}$ by setting (s_d, S_d) to the realized value.

Second, regarding the urban households' migration, the relative changes satisfy:

$$
\hat{\mu}_{u,o,d} = \hat{\eta}_o \cdot \frac{(\hat{P}_o \cdot \delta_{o,d} + \hat{w}_d \cdot (1 - \delta_{o,d}))^{\epsilon^u} \cdot \hat{P}_d^{-(1-\alpha)\gamma\epsilon^u}}{\sum_i \lambda_{u,o,i} \cdot (\hat{P}_o \cdot \delta_{o,i} + \hat{w}_i \cdot (1 - \delta_{o,i}))^{\epsilon^u} \cdot \hat{P}_i^{-(1-\alpha)\gamma\epsilon^u}}, \ \forall n \neq i \tag{19}
$$

where

$$
\hat{\eta}_o = \frac{\ell\bar{L}_{u,o}(1 - s_o) + S_o(1 - mo_o)/\eta_o}{\ell\bar{L}_{u,o}(1 - s_o) + S_o(1 - mo_o)}. \tag{20}
$$

For $o = d$ so that these urban households do not migrate, we have

$$
\hat{\mu}_{u,o,o} = \frac{\mu'_{u,o,o}}{\mu_{u,o,o}} = \frac{1 - \sum_{d \neq o} \mu_{u,o,d}\hat{\mu}_{u,o,d}}{1 - \sum_{d \neq o} \mu_{u,o,d}}.
$$

For rural households, the relative changes of their migration share satisfy:

$$\hat{\mu}_{r,o,d} = \frac{\hat{w}_d^{\epsilon^r} \cdot \hat{P}_d^{-(1-\alpha)\gamma\epsilon^r}}{\sum_i \lambda_{r,o,i} \cdot \hat{w}_i^{\epsilon^u} \hat{P}_i^{-(1-\alpha)\gamma\epsilon^r}}, \forall n \neq i. \tag{21}$$

And if $o = d$ (that is to say they do not migrate) then we have

$$\hat{\mu}_{r,o,o} = \frac{\mu'_{r,o,o}}{\mu_{r,o,o}} = \frac{1 - \sum_{d \neq o} \mu_{r,o,d} \hat{\mu}_{r,o,d}}{1 - \sum_{d \neq o} \mu_{r,o,d}}.$$

To summarize, housing prices and migration will be jointly determined in equilibrium, by solving Equation (18), (19) and (21). Housing price changes will affect the households' migration network, which, in return, will affect the supply and demand of housing and hence housing prices in each city. For now, we will take the change of wages, $\hat{w}$, as exogenous.

4.4 Parameter Calibration and Estimation

This section details the calibration and estimation of the parameters from the model.

Calibration. $\bar{H}_o$ is the quality-adjusted size of shanty homes in city o. It is quality-adjusted so that its unit price is the same as other homes. Using the 2015 Population 1% Survey, we first identify shanty homes as those built before 2000 and calculate the average home floor area for each city. We then use the CDB loan data and find that the amount of cash compensation per square meter is about 70% of the second-hand housing prices in our data. We therefore multiple the average home floor area of shanty homes by 70% to construct the quality-adjusted home size.

In the model, w_i and w'_i are the present value of the household life-time wage at any city i in both periods. Suppose each household involves two labors working for 40 years. We extrapolate future wages by fitting a city-specific AR(1) process with drift to the time series of wages. Specifically, we estimate the following model:

$$\ln(wage_{i,t}) = \alpha_i + \beta_i \ln(wage_{i,t-1}) + \theta_i t + \varepsilon_{i,t}.$$

For households who migrate in year t, we calculate the present value of the households' lifetime wages as

$$pv_{i,t} = 2 \sum_{\tau=1}^{40} \frac{wage_{i,t}}{(1+R)^t}$$

We assume the annual discount rate is $R = 5\%$. The first period $t = 1$ corresponds to the period of 2011-2015, and hence we calculate the average lifetime wages of households that migrate during this time period as: $w_1 = \frac{1}{5} \sum_{t=2011}^{2015} pv_{i,t}$. Similarly for $t = 2$, we have $w_2 = \frac{1}{5} \sum_{t=2016}^{2020} pv_{i,t}$.

$1 - \alpha$ is the share of spending on housing for those who rent. Based on the China Statistical Yearbook of 2014, the share of household spending on housing, which is mainly relevant for renters, is about 22.5%. So $\alpha = 1 - 22.5\% = 0.775$.

$1 - \alpha\gamma$ is the share of spending on housing for those that purchased homes. Based on the observed size of shanty homes and homes built after 2000 and purchased by urban households, combined with the local urban wages, we can direct calculate $1 - \alpha\gamma$ as a fraction between value of new homes and $w_{1,i} + P_{i,2014} \cdot \bar{H}_i$, which is about 28.7%. Therefore, $\gamma = \frac{1-28.7\%}{\alpha} = 92.0\%$.

a relates to the equilibrium size of speculative capital. We calibrate a such that the average equilibrium housing price growth in the model equals the value in the data. We get $a = 0.48$.

R is the minimum required rate of return for those speculators. We use the accumulated return of bank WMPs during 2016-2020, which is about 1.246.

Migration Elasticity. For other parameters, we estimate their value using various regression analysis. First, we obtain the migration elasticities $(\epsilon^u, \epsilon^r, \phi^u, \phi^r)$ from the following steps.

We can write $(\mu_{u,o,d}, \mu_{r,o,d})$, $\forall o \neq d$, as follows

$$\mu_{u,o,d} = \exp\big(\ln(\eta_o) + \epsilon^u \ln(wp_{u,o,d}) - \epsilon^u \phi^u \ln(\kappa_{o,d}) - \ln(A_{u,o})\big),$$

$$\mu_{r,o,d} = \exp\big(\ln(\xi_o) + \epsilon^r \ln(wp_{r,o,d}) - \epsilon^r \phi^r \ln(\kappa_{o,d}) - \ln(A_{r,o})\big),$$

where $wp_{u,o,d} = (w_d + P_o \bar{H}_o) \cdot P_d^{-(1-\alpha)\gamma}$, $wp_{r,o,d} = w_d \cdot P_d^{-(1-\alpha)\gamma}$, $A_{u,o} = \sum_i (wp_{u,o,i})^{\epsilon^u} \kappa_{o,i}^{-\epsilon^u \phi^u}$, and $A_{r,o} = \sum_i (wp_{r,o,i})^{\epsilon^r} \kappa_{o,i}^{-\epsilon^r \phi^r}$.

Assume for both $g \in \{u, r\}$, the observed migration share, $\tilde{\mu}_{g,o,d}$, takes the form of $\tilde{\mu}_{g,o,d} = \mu_{g,o,d} + \varepsilon_{g,o,d}$. We can then use the *ppmlhdfe* package in Stata to estimate the following equation using city-pairs of which $o \neq d$:[18]

$$\tilde{\mu}_{g,o,d} = \exp(\alpha_{g,o} + \epsilon^g \ln(wp_{g,o,d}) - \epsilon^g \phi^g \ln(\kappa_{o,d})) + \varepsilon_{g,o,d},$$

which we estimate based on observed migration share during 2011-2015. The estimation delivers $\hat{\alpha}_{g,o}$, $\hat{\epsilon}^g$ and $\hat{\phi}^g$.

Housing Market Liquidity. We can back out η_o using the following relation:

$$\eta_o = \exp(\alpha_{u,o}) \cdot A_{u,o} = \exp(\alpha_{u,o}) \cdot \sum_i (wp_{u,o,i})^{\epsilon^u} \kappa_{o,i}^{-\epsilon^u \phi^u} \tag{22}$$

Similarly, we can also back out ξ_o using the following relation:

$$\xi_o = \exp(\alpha_{r,o}) \cdot A_{r,o} = \exp(\alpha_{r,o}) \cdot \sum_i (wp_{r,o,i})^{\epsilon^r} \kappa_{o,i}^{-\epsilon^r \phi^r} \tag{23}$$

Regarding $\kappa_{o,o}$, for each city we calculate the geographic distance between any two counties within this city and calculate the average county-pair distance weighted by the product of the two counties' downtown urban land size.

Migration Size. Conceptually, $(\bar{L}_{u,o}, \bar{L}_{r,o})$ is the number of all households that make the migration decisions. We measure them using the total number of households that changed their residence location (including both within-city and across-city migrants) during 2011-2015.

We assume $\bar{L}'_{r,o} = \bar{L}_{r,o}$. For $\bar{L}'_{u,o}$, we estimate them with extrapolation by running the

[18]The package *ppmlhdfe* stands for the estimation method with Pseudo Poisson Maximum-Likelihood High-Dimensional Fixed Effect.

following regressions in the cross section:

$$\frac{\tilde{L}_{u,o}}{N_o} = \beta \frac{S_o(1 - mo_o)}{N_o} + \ell \frac{\bar{L}_{u,o}(1 - s_o)}{N_o} + \varepsilon_o$$

where $\tilde{L}_{u,o}$ is the actual number of households that left their hukou address during 2016-2020, and N_o is the total number of households originating from and living in city o in 2015. We find that $\hat{\beta} = 1.215$ and we take it as 1. We find $\ell = 1.659$.

Housing Supply. To measure the size of new housing supply, in particular how it relates to the size of homes demolished, we run the following regression in the cross section:

$$H_i' = \rho_1 H_i + \rho_2 \cdot S_i \bar{H}_i,$$

where H_i' is the observed total new home sales during 2016-2020 in city i. We find $\rho_1 = 1.27$ and $\rho_2 = 0.97$.

5 Quantitative Analysis and Policy Evaluations

5.1 Model Implications

Now, we use the parameter estimates to simulate the quantitative model to explore the role played by the cash-based resettlement. We show that the cash-based resettlement leads to a more dispersed distribution of housing price growth across cities, with cities with higher initial housing prices experiencing faster price growth.

5.1.1 Model Fitness

We test the model's fitness by evaluating the difference between the model-predicted housing price growth and the observed housing price growth. As we interpret $t = 1$ as corresponding to 2011-2015 and $t = 2$ to 2016-2020, we calculate the average housing prices during 2011-15 and 2016-20 and then calculate the observed housing price growth

Table 5: Evaluating Model Fitness

	Data	Model	Data	Model
Dep Var: hp growth	(1)	(2)	(3)	(4)
loan_orig	-0.0344*	-0.0471***		
	(-1.702)	(-4.767)		
loan_dest	0.829*	0.695***		
	(1.819)	(4.090)		
$log(P)$			0.208***	0.181***
			(3.434)	(9.196)
Prov FE	Yes	Yes	Yes	Yes
Observations	252	252	252	252
R-squared	0.465	0.413	0.503	0.506

between these two periods. The correlation between the model-predicted and observed housing price growth is 0.1734.[19]

Our main interest is whether our model can capture the effect of cash-based resettlement at the originating and destination cities. To this end, we regress the observed and model-predicted housing price growth on *loan_orig* and *loan_dest* after controlling for the province-level fixed effect. Table 5 shows the regression results. We find that our simple model matches both sign and magnitude of the spatial variation along measures of cash-based resettlement.

In Column (3)-(4), we regress the observed and model-predicted housing price growth on $log(P)$, where P is the average housing prices during 2011-2015. The estimated coefficients are both significantly positive and similar in magnitudes. Therefore our model is able to capture the spatial variation in housing price growth across cities with differential initial housing prices.

5.1.2 Aggregate Effect of Cash-based Resettlement

We calculate the effect of the program on housing prices as $\hat{P} - \hat{P}^e$. To assess the aggregate impact of cash-based resettlement, we first compute the average housing price

[19]Figure A.1 of Appendix B plots the two price growth across different cities.

growth across cities, defined as a simple mean of $\hat{P} - \hat{P}^e$ in all cities. Our model indicates that, the average housing price growth due to the shantytown renovation program with cash-based resettlement is 4.70%, or 378.39 RMB per square meter. The model also implies that rational speculators account for 8.90% of home purchases during 2011-2015.

Next, we calculate the housing price effect across households, defined as the simple mean of households' housing price increases across all households. Given the varying sizes of housing markets across cities, the housing price growth across households is effectively a weighted average, with each city's market size as the weight. The average housing price growth across households is 7.10% or 701 RMB per square meters.

Finally, we also compute the households' average leverage, defined as the mean of households' home purchase spending divided by the cash compensation that they receive. The model implied household leverage is 2.52. Since we use lifetime discounted wage to simulate the model, households generally spend more on purchasing houses than the cash they receive in shantytown renovation programs. The difference can be thought of as mortgage financing. Since the total scale of shantytown renovation program is more than 4 trillion RMB, this leverage suggests that the total contribution to house demand is more than 10 trillion RMB, which was considerably large compared to the fact that the outstanding scale of household mortgage in 2015 was 14.18 trillion RMB.

5.1.3 Spatial Variation of the Effect

Although the aggregate effect of cash-based resettlement seems not very large, the spatial variation of the effect is considerable. Figure 8 shows the model-predicted housing price growth across different cities. The left figure shows that the predicted housing price growth is generally lower for cities with larger scale of shantytown renovation featuring cash-based resettlement. This is because cash-based resettlement allows recipients to move out and more new houses will be supplied than demolished. Thus, housing supply will increase more than housing demand does.

The right figure shows that the predicted housing price growth is higher for cities with higher average housing price in 2011-2015. There are two reasons for this. First, cities with lower housing prices had larger-scale cash-based resettlement than cities with

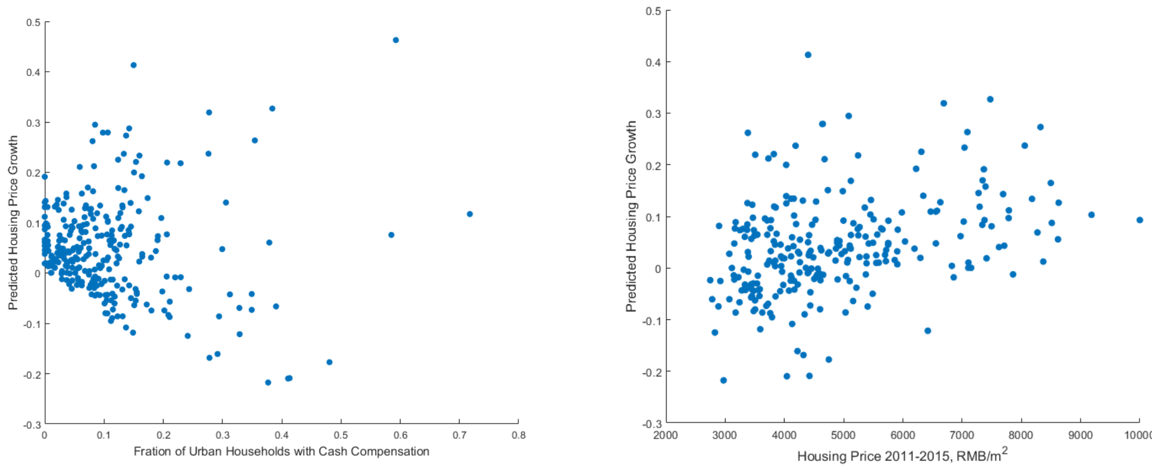


Figure 8: Policy Effect Across Cities

Note: The left figure shows the model predicted house price growth for cities with different fractions of urban households receiving cash compensation. The right figure shows the model predicted house price growth for cities with different average housing price level during 2011-2015.

higher housing prices. Second and more importantly, households tend to migrate from low-price cities to high-price cities. In the data, around 90% of migrants moved to cities with higher wages and higher housing prices. The cash-based resettlement facilitated urban migration and led to more money flow from low-price to high-price cities, which results to the positive correlation between initial housing price and price growth. In Figure 11 we will show that after shutting down the money migration, this positive correlation largely disappears.

Figure 9 illustrates the spatial reallocation of CDB loans across cities. We sort the cities into 10 groups based on their housing price in 2011-2015. The solid blue line represents the amount of CDB loans originated in cities in that group, the dashed blue line represents the amount of CDB loans that either flow to cities through migration or originated and stayed in cities in that group. The orange line represents the ratio between the two for each group. Our analysis reveals that cities in the top two groups which consists of 59 cities have an inflow-to-origination ratio exceeding 1, indicating a net inflow of CDB loans. Conversely, all other cities exhibit a ratio below 1, indicating a

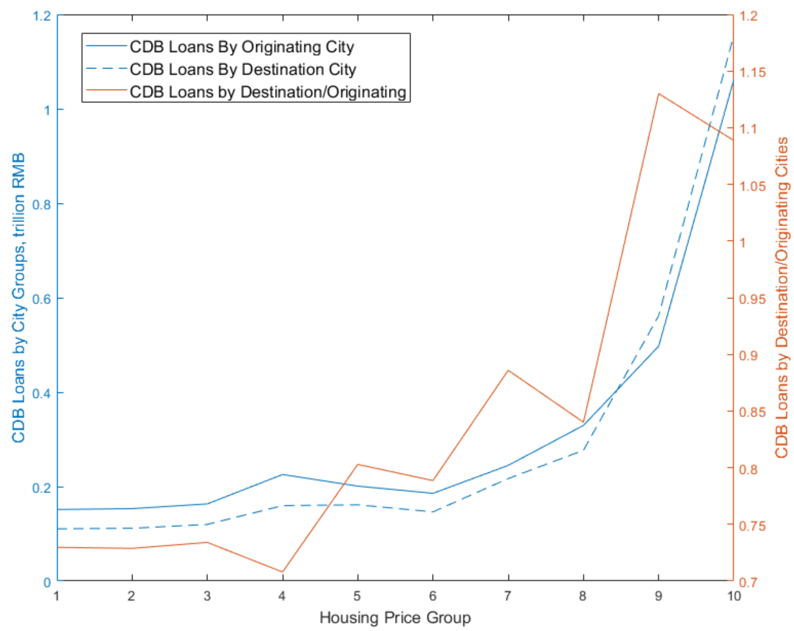


Figure 9: Spatial Reallocation of CDB Loans by City Groups

Note: The x-axis sorts the cities into 10 groups based on their average housing prices during 2011-2015. The solid blue line represents the amount of CDB loans originated in cities in that group, and the dashed blue line represents the amount of CDB loans that either flow to cities through migration or originated and stayed in cities in that group. The orange line represents the ratio between the two for each group.

net outflow of CDB loans. The bottom four groups of cities had a net outflow of more than 25% of CDB loans originated in their cities. Therefore, although the cash-based resettlement were primarily implemented in lower-tier cities, a significant fraction of the funds flowed to higher-tier cities.

Figure 10 further illustrates the reallocation of CDB Loans by showing the loan flows in city-pair. The x axis represents the originating city, while the y axis represents the destination city. The cities are still divided into 10 groups based on their housing price in 2011-2015. The z axis is the share of CDB loans that flow from the originating city to the destination city. We can still see that destination cities with the highest housing price in 2011-2015 received the largest amount of CDB loans.

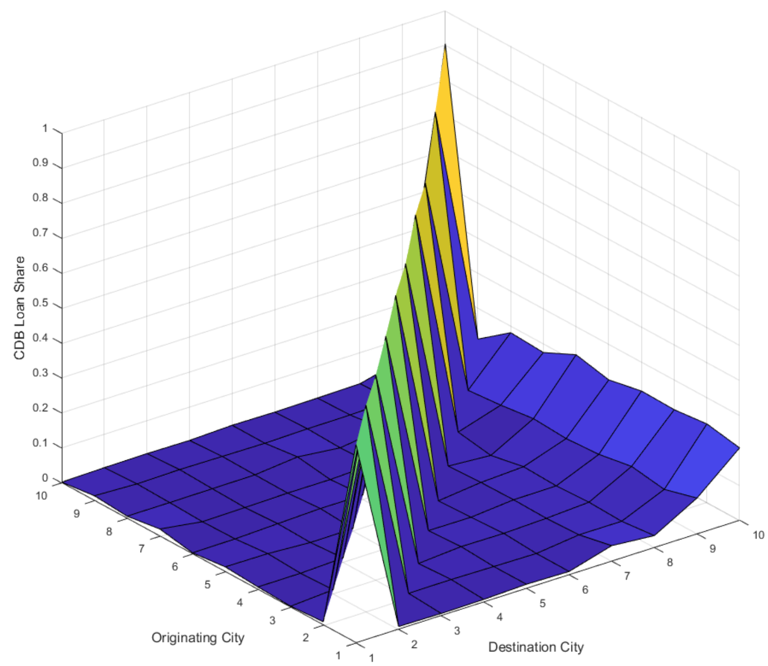


Figure 10: City Pairwise Reallocation of CDB Loans

Note: The x-axis represents the originating cities sorted into ten groups based on their average housing prices during 2011-2015, while the y-axis represents the destination cities with the same sorting. The z-axis is the share of CDB loans that flow from the originating cities to the destination cities.

These findings have significant implications for China's housing regulation and macroprudential policies. First, while the cash-based resettlement policy aims to bolster housing demand in lower-tier cities, it is the top-tier cities that actually experienced the increase of housing demand by immigrants that came from those lower-tier cities. As the policy also increase housing supply, although with some lag, lower-tier cities actually experienced smaller price increase due to the policy. The liquidity afforded to shanty owners by the renovation program facilitates their migration to other cities, and the significant house price drops in these cities may result in defaults by real estate firms and distress among banks.

Besides, the fiscal dynamics of repaying shantytown renovation loans involve transfer payments from lower-tier cities to top-tier cities, which undermines or even negates the intended effect of redistributing wealth from richer to poorer cities. This may lead to financial stringency in lower tier cities.[20]

Housing regulation and macroprudential policies must account for the risk of housing market crashes induced by the shantytown renovation program. Local governments, driven by short-term incentives, may excessively pursue shantytown renovation due to its immediate benefits in raising land prices and fiscal income. Therefore, macroprudential policies should enforce stricter regulations at the initial stages of shantytown renovation to mitigate future financial instability.

5.2 Counterfactual: Voucher-based Resettlement

5.2.1 Voucher-based Resettlement versus Cash-based Resettlement

Recognizing the issues in shantytown renovation, some local governments have used an alternative resettlement approach: the "housing voucher-based resettlement." Under this scheme, the government does not provide cash to households. Instead, households receive a voucher which can only be used to purchase existing houses within a designated area. By restricting voucher usage to local purchases, the policy curtails migration of the compensation recipients.

To assess how endogenous migration by households who received the cash compensation has shaped the spatial impact of the cash-based resettlement, we take the voucher-based resettlement into the model. We assume that the voucher resettlement allows the households to buy houses only in their originating city. For simplicity, we assume there is no secondary market for vouchers.

We can think of the voucher-based resettlement as lowering η'_o. That is, for those that receive the vouchers, they cannot migrate, and hence the average fraction of urban

[20] Appendix C provides a more detailed discussion on the fiscal implications of our results.

households that are free to make migration decision is:

$$\eta_o' = \frac{\ell \bar{L}_{u,o}(1-s_o)\eta_o}{\bar{L}_{u,o}'}$$

The relative change of housing liquidity for urban migrants therefore becomes:

$$\hat{\eta}_o = \frac{\ell \bar{L}_{u,o}(1-s_o)}{\ell \bar{L}_{u,o}(1-s_o) + [\beta_2 S_o(1-migout_o)]}$$

All other expressions for the exact hat algebra remain the same, and we can solve the model under this alternative policy as we did before.

Household Surplus. To evaluate how the voucher-based resettlement affects household welfare, we can calculate the household willing-to-pay (wtp) to switch from voucher-based to cash-based resettlement. For urban household migrants who are free to migrate either due to successfully selling their homes or receiving the cash compensation, the expected surplus from their optimal choice is:

$$E[\max_i V_{o,d}^u] = \ln\Big(\sum_{d=1}^{N}(\frac{w_d + P_o\bar{H}_o}{P_d^{(1-\alpha)\gamma}})^{\epsilon^u} d_{o,d}^{-\epsilon^u\phi^u}\Big) + Z,$$

where Z is some constant. For households who cannot migrate to other cities, we have

$$E[V_{o,o}^u] = \ln\Big((\frac{w_o + P_o\bar{H}_o}{P_o^{(1-\alpha)\gamma}})^{\epsilon^u} d_{o,o}^{-\epsilon^u\phi^u}\Big) + Z$$

Denote the corresponding housing price under cash-based and voucher-based resettlement as P^c and P^v. We can now calculate the willingness-to-pay for different types of urban households.

First, for any given city o, $\ell \bar{L}_{u,o}(1-s_o)\eta_o$ is the number of urban households that are free to migrate regardless of the resettlement approach. Denote their dollar value of wtp as $wtp_{o,1}$, which is the dollar amount that they are willing to pay to go from a world with cash-based resettlement to a world with voucher-based resettlement. We shall interpret

$wtp_{o,1}$ as that in the voucher-based settlement world, after paying $wtp_{o,1}$ the households redo their migration optimization problem and end up with the same expected utility as they receive in the cash-based resettlement world. We have

$$\ln\Big(\sum_{d=1}^{N}(\frac{w'_d + P_o^v \bar{H}_o - wtp_{o,1}}{(P_d^v)^{(1-\alpha)\gamma}})^{\epsilon^u} d_{o,d}^{-\epsilon^u \phi^u}\Big) = \ln\Big(\sum_{d=1}^{N}(\frac{w'_d + P_o^c \bar{H}_o}{(P_d^c)^{(1-\alpha)\gamma}})^{\epsilon^u} d_{o,d}^{-\epsilon^u \phi^u}\Big).$$

Second, $\ell \bar{L}_{u,o}(1-s_o)(1-\eta_o)$ is the number of urban households that are not free to migrate regardless of the resettlement approach. Similarly, their willing-to-pay to go from a cash-based resettlement world to a voucher-based resettlement world, $wtp_{o,2}$, satisfies:

$$\ln\Big((\frac{w'_o + P_o^v \bar{H}_o - wtp_{o,2}}{(P_o^v)^{(1-\alpha)\gamma}})^{\epsilon^u} d_{o,o}^{-\epsilon^u \phi^u}\Big) = \ln\Big((\frac{w'_o + P_o^c \bar{H}_o}{(P_o^c)^{(1-\alpha)\gamma}})^{\epsilon^u} d_{o,o}^{-\epsilon^u \phi^u}\Big).$$

Finally, $S_o(1-mo_o)$ is the number of urban households that are free to migrate only under cash-based resettlement but not voucher-based resettlement. Their willing-to-pay to go from a cash-based resettlement world to a voucher-based resettlement world, $wtp_{o,3}$, satisfies:

$$\ln\Big((\frac{w'_o + P_o^v \bar{H}_o - wtp_{o,3}}{(P_o^v)^{(1-\alpha)\gamma}})^{\epsilon^u} d_{o,o}^{-\epsilon^u \phi^u}\Big) = \ln\Big(\sum_{d=1}^{N}(\frac{w'_d + P_o^c \bar{H}_o}{(P_d^c)^{(1-\alpha)\gamma}})^{\epsilon^u} d_{o,d}^{-\epsilon^u \phi^u}\Big).$$

5.2.2 Model-based Policy Evaluation

Figure 11 compares the model-predicted housing price growth under cash-based resettlement with that under voucher-based resettlement. The left figure shows the case under cash-based resettlement, which is identical to the left figure in Figure 8. The right figure shows the case under voucher-based resettlement. A notable difference is that under voucher-based resettlement, the negative correlation between housing price growth and the size of the shantytown renovation programs largely disappears. If anything, the correlation becomes positive. This is consistent with the intuition that voucher-based resettlement forces shanty owners to purchase houses in the originating cities, which shuts down the negative effects on housing prices due to emigration.

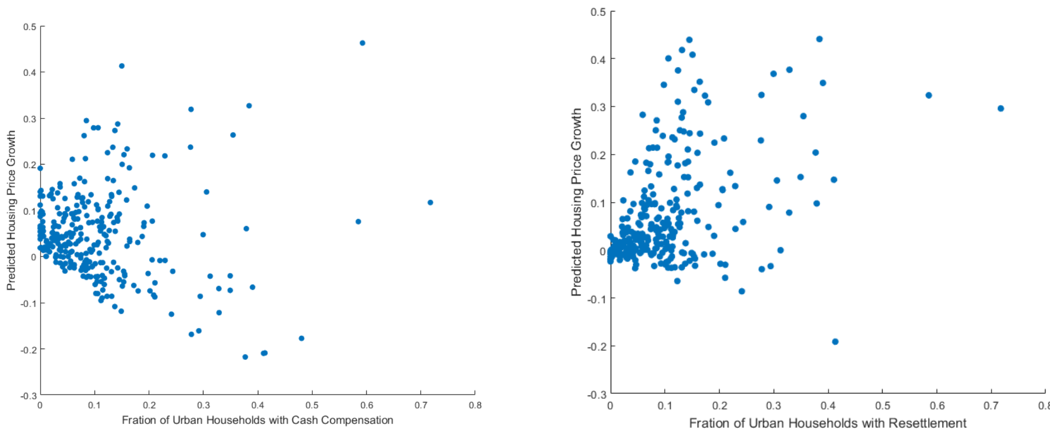


Figure 11: Cash-based vs Voucher-based resettlement

Note: The left figure shows the model predicted housing price growth for cities with different fractions of urban households receiving cash compensation. The right figure shows the model predicted housing price growth for cities with different fractions of urban households receiving voucher resettlement.

Figure 12 further investigates the reallocation effect of cash-based resettlement. The dispersion of housing price growth across different city groups significantly decreases with the introduction of voucher-based resettlement. The intuition is straightforward: cities with lower housing prices during 2011-2015 had larger scales of shantytown renovation programs but were mostly originating cities with more emigrants. Therefore, if the voucher-based resettlement program forces shanty owners to remain in their current cities, then these cities will experience higher housing price growth due to reduced outflow of funds. This results in a flatter curve of predicted housing price growth relative to previous housing prices. The gap of the housing price growth between the group of cities with the highest housing prices in the past and the group of cities with the lowest housing prices in the past under cash-based resettlement is approximately 20%. By contrast, the gap is about 9% under voucher-based resettlement.

However, although voucher-based resettlement reduces the dispersion of housing price growth, it does not necessarily improve social welfare due to less efficient labor allocation. The average household surplus decreases by 168,521.38 RMB or 9.85% of their lifetime wage because voucher-based resettlement prevents households from migrating

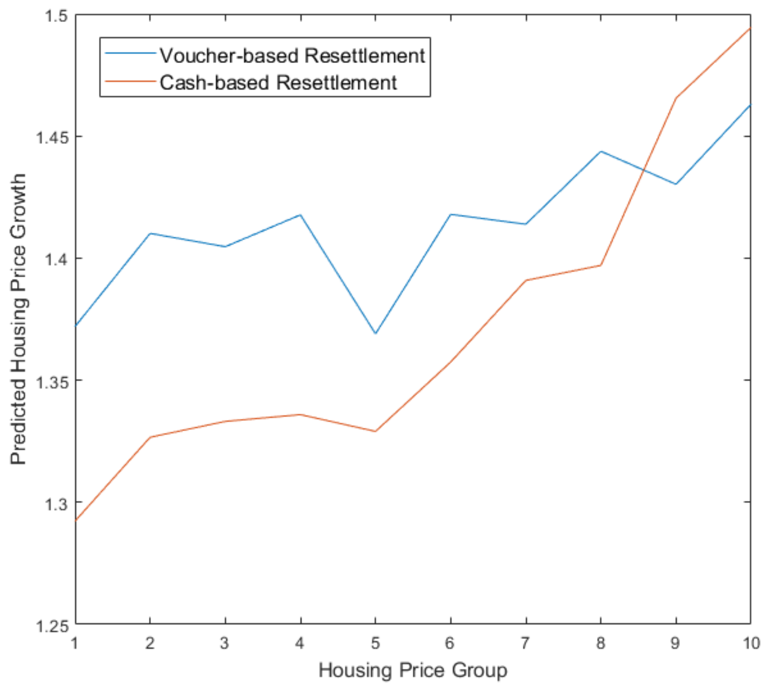


Figure 12: Housing Price Growth Under Cash-based vs Voucher-based Resettlement

Note: The x-axis sorts the cities into 10 groups based on their average housing prices during 2011-2015. The orange line represents the model predicted housing price growth with cash-based resettlement, and the blue line represents the model predicted housing price growth with voucher-based resettlement.

to cities with higher wages. This creates a trade-off between labor allocation efficiency and housing market stability. Allowing shanty owners to move freely enhances labor allocation efficiency but may cause sharp housing price drops in small cities. Conversely, preventing shanty owners from moving freely stabilizes the housing market but sacrifices labor allocation efficiency.[21]

[21] see Hsieh and Moretti (2019) for more discussion about the relationship between housing constraints and spatial misallocation of labor.

6 Conclusion

In this paper, we examine the effects of shantytown renovation programs and cash-based resettlement on the housing market in China. The reduced-form analyses suggest that the cash-based resettlement facilitated household migration by unlocking them from the illiquid housing market, which increased housing demand in destination cities and exacerbated the decline in housing demand in originating cities. Consequently, cities implementing the program experienced lower housing price growth and more severe supply overhang, while cities receiving the migrants saw higher housing price growth, lower inventory and more housing speculation.

We then employ a spatial equilibrium model to simulate the dispersion of house price growth across cities under the shocks of shantytown renovation programs. The counterfactual analysis indicates that housing price growth in cities with the highest past housing prices is 20% higher than in cities with the lowest past housing prices due to the implementation of shantytown renovation programs with cash-based resettlement. Voucher-based resettlement, by forcing compensation recipients to purchase local houses, can significantly reduce the dispersion of housing price growth but at the cost of labor allocation efficiency.

While this paper primarily focuses on the effects of shantytown renovation programs and cash-based resettlement on housing market prices and inventories, the implications for financial fragility are also crucial to explore. An important direction for future research is to extend the model to incorporate negative shocks to the housing market and study the stability of housing markets and the fiscal capacity of local governments. This could provide a better understanding of Chinas current housing market recession.

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Online Appendix

A Supplementary Material for Section 2

Table A.1: Variable Definition

Variable	Definition
P	ask price of second-hand homes, RMB per sqm.
q	floor area of annual residential land supply scaled by housing market transacted area in 2014.
inv2area	estimated size of land and home inventory held by home developers at the year beginning scaled by housing market transaction area in 2014.
loan_orig	the local amount of CDB (China Development Bank) loans scaled by housing market transaction value in 2014.
loan_dest	the inflow of CDB (China Development Bank) loans scaled by housing market transaction value in 2014.
demolish	demolished floor area of shanty homes scaled by housing market transacted area in 2014.
Loan2NP	total CDB loans at originating city per household scaled by hpsec in destination city in 2014. Unit: sq.m.
price2rent	price-to-rent ratio.
buyintent	dummy equals 1 if the household intends to buy homes in the future.
fore2sale	total floor area of foreclosed homes in 2022 scaled by average housing market transacted area during 2015-2021.

Table A.2: Home Demolished during the Shantytown Renovation Program

Dep Var: demolish	(1)
loan_orig	1.593***
	(8.776)
Prov FE	Yes
Observations	239
R-squared	0.590

Note: This table reports the correlation between *loan_orig* and the floor area of homes demolished under shantytown renovation projects financed by all the CDB loans used to construct *loan_orig*. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.3: Local Household Intention of Buy Homes

Dep Var: buyintent	(1)	(2)	(3)	(4)
Year	2013	2015	2017	2019
loan_orig	-0.00242	-0.0230***	-0.0141***	-0.00425
	(-0.344)	(-3.472)	(-2.869)	(-0.983)
loan_dest	0.112	0.313**	0.494***	0.211**
	(0.710)	(2.447)	(3.543)	(1.979)
Prov FE	Yes	Yes	Yes	Yes
Observations	21,177	13,525	31,092	23,877
R-squared	0.011	0.007	0.008	0.006
#Cities	140	145	146	138

Note: This table reports the effect of *loan_orig* and *loan_dest* on the local household intention to purchase homes in the future. The sample is from the China Household Finance Survey and only includes households with hukou in their residence city, regardless of whether or not they made any home purchase since 2000. Standard errors are clustered by city. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Supplementary Material for Section 5

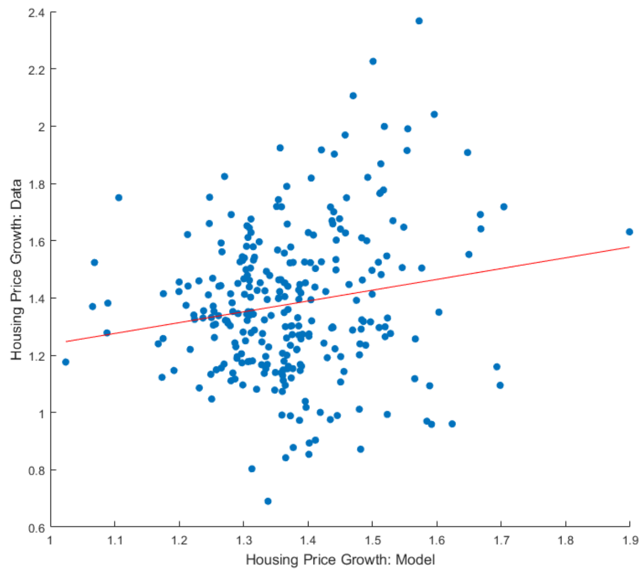

Figure A.1: Housing Price Growth: Model vs Data

Note: This figure shows the model predicted house price growth over the actual house price growth in each city from 2016-2020. Vertical axis shows the actual house price growth in the data, while the horizontal axis is the model predicted house price growth.

C Further Discussion on Fiscal Implications

The fiscal dynamics of repaying shantytown renovation loans involve transfer payments from lower-tier cities to top-tier cities, which undermines or even negates the intended effect of redistributing wealth from richer to poorer cities. This may lead to financial stringency in lower tier cities.

Specifically, in the shantytown renovation programs, local governments established platform firms that borrowed funds from the CDB to implement shantytown renovations. According to the loan agreements, local governments were responsible for repaying these loans through fiscal revenues. Therefore, shantytown renovation debts are explicitly classified as local government debt.

Given that we have shown cash-based resettlement enables households from lower-tier cities to migrate to top-tier cities, these households transfer their funds and purchase houses in top-tier cities. Consequently, land prices in top-tier cities rise, allowing local governments to generate substantial revenue from land sales. This revenue equips top-tier city governments with ample resources to repay loans from CDB. However, lower-tier cities face declining land prices, hampering their ability to raise sufficient funds in the future, potentially leading to financial distress.

Note that there are no explicit defaults on shantytown renovation loans until now. Figure A.2 illustrates that the majority of shantytown renovation loans have yet to mature. A plausible explanation is that provincial capital cities have the largest amount of matured shantytown renovation loans. Given their significance, provincial governments are unlikely to permit defaults by these local governments. Additionally, the relatively small proportion of matured shantytown renovation loans makes it feasible for local governments to repay the debt using fiscal revenues at present. However, local governments, especially in lower-tier cities, may encounter more severe challenges around 2025 and 2030, as loans in many tier-3 and tier-4 cities will mature, and these cities have comparatively weaker fiscal capacities.

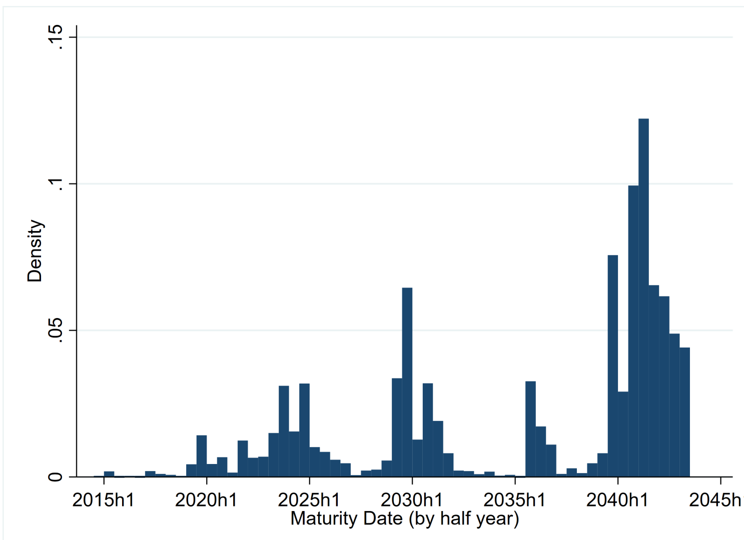

Figure A.2: Distribution of the Maturity Date of Shantytown Renovation Loans Issued in 2014-18