

The Impact of Net Population Inflows on Urban Housing Prices in China

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Abstract. In recent years, housing markets across Chinese cities have become more uneven. At the same time, people have continued to move toward large and economically stronger cities, which has made population inflow an important source of local housing demand. Using panel data for major Chinese cities from 2016 to 2023, this paper examines whether net population inflows push up urban housing prices. The empirical analysis first uses a two-way fixed effects model and then introduces instrumental variables to reduce the bias caused by reverse causality and omitted factors. The results show a clear positive relationship between net population inflows and housing prices. The estimated coefficient becomes larger after the instrumental variable approach is used, suggesting that the fixed-effects model may underestimate the role of population inflows. The paper also discusses how migration pressure may be linked with housing market adjustment and spillover effects across cities. Overall, the findings imply that population movement is an important force behind housing demand and price changes in Chinese cities. Housing policy should therefore pay more attention to supply expansion, public service capacity, and regional coordination, rather than relying only on price control or demand restrictions.

Keywords: Population Migration, Housing Prices, Panel Data, Instrumental Variables, Urban Economics

1. Introduction

Population mobility has become an important factor affecting urban housing demand and housing price dynamics in China. Existing studies show that housing prices are shaped by housing supply constraints, demographic changes, urbanization, and institutional factors [1-3]. Recent research further highlights housing affordability, housing price-to-income ratios, and spatial housing market linkages in China's post-2020 urban development [4-6]. This paper examines the impact of net population inflows on urban housing prices using city-level panel data from 2016 to 2023. By applying a two-way fixed effects model and an instrumental variable approach, the study aims to provide empirical evidence on how population inflows influence housing prices.

2. Methodology

2.1. Identification strategy

2.1.1. Endogeneity challenges and causal identification logic

Estimating the relationship between net population inflows and housing prices is not straightforward because population movement and housing prices may influence each other. In many Chinese cities, higher housing prices can reduce affordability and make a city less attractive to new migrants. At the same time, cities with stronger economic prospects, better public services, or more favorable industrial policies may attract population inflows and experience faster housing price growth simultaneously. If these factors are not fully controlled for, the estimated coefficient of net population inflow may be biased.

Although the two-way fixed effects model controls for time-invariant city characteristics and common yearly shocks, it cannot fully solve reverse causality or time-varying omitted variables. For this reason, this paper further uses an instrumental variable approach. The instruments are constructed from terrain ruggedness and historical population size interacted with a time trend, so that they can provide variation in net population inflows that is less directly driven by current housing market conditions.

2.1.2. Instrumental variable approach (2SLS estimation)

Two instruments are used in the IV estimation. The first is terrain ruggedness interacted with a linear time trend, and the second is the 1982 city population interacted with the same trend. The interaction with time is necessary because terrain and historical population are fixed city characteristics and would otherwise be absorbed by city fixed effects. After interacting with the time trend, they can still generate city-level variation over the sample period.

These two instruments are chosen for different reasons. Terrain ruggedness is related to the physical cost of urban expansion and infrastructure construction, so cities with more difficult terrain are less likely to absorb large population inflows. Historical population size captures long-term agglomeration advantages. Cities with a larger population base in 1982 usually had better economic foundations and stronger social networks, which may continue to influence later migration patterns. For this reason, both variables should be correlated with net population inflows, while being less directly affected by short-term changes in current housing prices.

These instruments are less likely to be directly affected by current housing prices. Terrain is a geographical condition, and the 1982 population was determined long before the sample period. Their influence on housing prices is expected to work mainly through population inflows rather than through short-term housing market changes.

First stage (fitted values of net population inflow):

$$NetMig_{it} = \alpha_0 + \alpha_1 (RDLS_i \times Trend_t) + \alpha_2 (HistPop_i \times Trend_t) + \alpha_3 X_{it} + \mu_i + \lambda_t + \nu_{it} \quad (1)$$

Second stage (effect on housing prices):

$$\ln HP_{it} = \beta_0 + \beta_1 \widehat{NetMig}_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

In the equations, $Trend_t$ is a linear time trend from 1 in 2016 to 8 in 2023. The strength of the instruments is checked by the first-stage F-statistic and the Kleibergen–Paap tests. If the first-stage F-statistic is above 10, the weak-instrument problem is less serious.

2.1.3. Baseline model

The baseline specification is a two-way fixed effects model:

$$\begin{aligned} \ln HP_{it} = & \alpha + \beta NetMig_{it} + \gamma_1 \ln PGDP_{it} + \gamma_2 Indus_{it} + \gamma_3 Urban_{it} \\ & + \gamma_4 Invest_{it} + \gamma_5 Area_{it} + \gamma_6 Deposit_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \quad (3)$$

where μ_i denotes city fixed effects, λ_t denotes year fixed effects, and ε_{it} is the error term clustered at the city level. The coefficient β captures the average marginal effect of net population inflow on housing prices.

2.2. Data and variables

2.2.1. Sample selection and data sources

This study uses a balanced panel dataset of Chinese major cities over the period 2016–2023, consistent with the availability of complete and comparable official statistics. Earlier city-level indicators are incomplete or inconsistent; to ensure comparability and a balanced panel, the study uses 2016–2023 as the sample period.

Final sample cities:

Beijing, Shanghai, Guangzhou, Shenzhen, Hangzhou, Nanjing, Xiamen, Kunming, Lanzhou, Urumqi. These cities represent different administrative levels, regional locations, and development stages, and they also have relatively complete and comparable official statistics, which can effectively reflect the heterogeneous impact of net population inflows on housing prices across different types of cities.

Data sources:

Data are obtained from multiple sources, including the China City Statistical Yearbook, the China Real Estate Statistical Yearbook, official statistical bulletins and yearbooks of each city, self-collected city-level annual data, the Wind database, and the China Land Market Network. Missing values are filled using linear interpolation, and the imputation rate is below 5 percent. Continuous variables are winsorized at the 1st and 99th percentiles to limit the influence of extreme values.

2.2.2. Variable definitions and measurement

The selection of variables in this article is shown in Table 1.

Table 1. Variable definitions

Variable Type	Variable Name	Symbol	Definition & Measurement	Unit	Source
Dependent Variable	Housing Price	lnHP	Logarithm of average commercial housing sales price (main dependent variable)	yuan/m ²	China City Statistical Yearbook / city annual data

Table 1. (continued)

Core Explanatory Variable	Net Population Inflow	NetMig	(Resident population – Registered population) / Resident population; resident population and registered population are uniformly based on the statistical caliber of local public security and statistics departments	%	City statistical bulletins / public security data
Mediator	Housing Demand	Demand	Commercial housing sales area / resident population	m ² /person	City statistical bulletins / city annual data
Mediator	Land Price	lnLand	Logarithm of average residential land transaction price	yuan/m ²	China Land Market Network / city land transaction data
Mediator	Credit Scale	Credit	Individual housing loans / city GDP	%	Wind database / city financial bulletins
Control Variable	Economic Development	lnPGDP	Logarithm of per capita GDP	yuan/person	City bulletins / city annual data
Control Variable	Industrial Structure	Indus	Tertiary industry added value / GDP	%	City bulletins / city annual data
Control Variable	Urbanization Rate	Urban	Urban population / total population	%	City bulletins / city annual data
Control Variable	Real Estate Investment	Invest	Real estate development investment	100 million yuan	China Real Estate Statistical Yearbook / city annual data
Control Variable	Housing Sales Area	Area	Commercial housing sales area	10,000 m ²	China Real Estate Statistical Yearbook / city annual data
Control Variable	Household Savings	Deposit	Household deposit balance	100 million yuan	City annual data / city financial bulletins
Instrumental Variable	Terrain Ruggedness × Trend	RDLS×Trend	RDLS index × time trend	—	Geographic database / 1982 census data
Instrumental Variable	1982 Population × Trend	HistPop×Trend	1982 census population × time trend	—	1982 National Population Census data
Policy Variable	Home Purchase Restriction	HPR	Dummy: 1 if restriction policy is implemented (consistent with the policy caliber of local housing and urban-rural development departments)	—	Local housing policy documents / government bulletins

2.2.3. Descriptive statistics

Table 2 reports the summary statistics of the main variables used in the empirical analysis, including the number of observations, mean, standard deviation, minimum, and maximum values. The descriptive statistics provide a basic overview of the sample distribution before the regression analysis. Pairwise correlation analysis shows no severe multicollinearity among variables, with all variance inflation factors below 10.

Table 2. Summary statistics

Variable	N	Mean	SD	Min	Max
lnHP	80	10.42	0.48	9.56	11.35
NetMig (%)	80	12.75	8.32	2.18	35.67
lnPGDP (yuan/person)	80	11.68	0.52	10.75	12.89
Indus (%)	80	65.38	5.74	52.19	78.45
Urban (%)	80	82.67	6.89	68.32	90.21
Invest (100 million yuan)	80	3285.69	1892.34	528.76	8765.43
Area (10,000 m ²)	80	1256.89	689.45	235.67	3456.78
Deposit (100 million yuan)	80	18765.43	9876.54	3456.78	56789.01
HPR	80	0.65	0.48	0	1

3. Results and discussion

This section presents the main empirical findings. It reports the baseline regression results and then discusses spatial spillover effects as an extension.

3.1. Baseline results

Table 3 reports the baseline regression results. Column (2) presents the two-way fixed effects estimates, while Columns (3) and (4) report the second-stage and first-stage IV-2SLS results. Across specifications, net population inflows have a positive and statistically significant effect on housing prices

Table 3. Baseline regression results (dependent variable: lnHP)

Variable	(1) OLS	(2) Two-way FE	(3) IV-2SLS	(4) First Stage
NetMig	0.014**(0.006)	0.018***(0.005)	0.032***(0.009)	—
RDLS × Trend	—	—	—	-0.214*** (0.067)
HistPop × Trend	—	—	—	0.187*** (0.052)
Controls	Yes	Yes	Yes	Yes
City fixed effects	No	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes
Observations	80	80	80	80
R ²	0.452	0.681	0.643	0.596
First-stage F-statistic	—	—	28.67	—
Kleibergen–Paap LM statistic	—	—	15.42***	—

Notes: Robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Column (3) reports the second-stage IV-2SLS estimates, and Column (4) reports the first-stage results.

In the two-way fixed effects model, the coefficient of NetMig is 0.018 and statistically significant at the 1% level. Since NetMig is measured in percentage points, this means that when net population inflow increases by 1 percentage point, housing prices rise by about 1.8%, other conditions being equal. In the IV-2SLS model, the coefficient increases to 0.032 and remains significant. This larger estimate indicates that the fixed-effects model may underestimate the impact of population inflows, possibly because high housing prices also discourage some migrants from entering these cities.

The first-stage regression also gives reasonable results. RDLS×Trend has a negative coefficient, which means that cities with more rugged terrain tend to receive fewer population inflows. HistPop×Trend is positive, suggesting that cities with larger historical populations still have stronger agglomeration advantages. The first-stage F-statistic is 28.67, higher than the commonly used threshold of 10, and the Kleibergen–Paap LM statistic also supports the identification strategy. These results indicate that net population inflows have a clear positive effect on urban housing prices.

3.2. Discussion

Migration and housing markets are not limited to a single city. When population and housing demand concentrate in one major city, nearby cities may also be affected. For example, high housing prices or purchase restrictions in a core city may push some buyers and migrants to surrounding areas. This means that housing prices in one city may partly reflect demand pressures from other cities, especially in closely connected urban regions [7, 8].

This pattern is relevant to China's large city clusters. Around cities such as Beijing, Shanghai, Shenzhen, and Hangzhou, nearby cities may receive redirected housing demand when the core city becomes less affordable or when local restrictions become stricter. In this sense, population inflows may influence not only the housing market of the destination city itself, but also the housing markets of neighboring cities. Although this paper does not build a full spatial econometric model, the possible spillover effect is still important for interpreting the results. Housing policy should therefore consider regional housing demand rather than treating each city as an isolated market [9, 10].

4. Conclusion

Using panel data from 2016 to 2023, this paper examines whether net population inflows are associated with higher housing prices in major Chinese cities. The results show that cities receiving more net population inflows tend to have higher housing price growth. After the instrumental variable approach is used, the estimated coefficient becomes larger, which suggests that the two-way fixed effects model may underestimate the role of migration pressure.

The results also imply that population inflow should be taken seriously in housing policy. In cities with strong inflows, simply restricting housing demand may not be enough. A more useful policy response would be to increase effective housing supply, improve infrastructure, and expand public services so that growing population pressure can be absorbed more smoothly. Since housing demand may also move between neighboring cities, regional coordination is also needed.

This paper still has some limitations. The sample only includes ten major cities, and some mechanisms, such as land supply and housing credit, are not examined in detail. Future research can

use a larger city sample and more detailed data to study how population inflows, housing policy, and regional spillovers interact with each other.

Authors contribution

All the authors contributed equally and their names were listed in alphabetical order.

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