Housing Prices, Internal Migration, and Intergenerational Mobility*

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Abstract

This paper examines how housing affordability affects intergenerational mobility in China by influencing internal migration. It also explores whether housing policies can mitigate the challenges that rising housing costs pose to social mobility and inequality. To address the endogeneity of housing prices, I employ an instrumental variables approach, exploiting the Housing Purchase Restriction policy as a natural experiment. This policy limited the number of properties households could purchase in selected prefectures, thereby creating quasi-exogenous variation in housing price growth. I find that higher housing costs deter migration, with a more pronounced effect on individuals from disadvantaged families. As a result, these individuals earn lower incomes than their counterparts from more affluent backgrounds. Therefore, higher housing costs reduce intergenerational mobility. To rationalize the findings, I build a theoretical model in which housing costs place a disproportionate burden on individuals from disadvantaged families. Furthermore, to distinguish among destinations and evaluate the effects of various housing policies, I adopt a structural approach to complement the aggregate-level reduced-form results. Unlike the reduced-form analysis, the structural approach reveals that the impact varies across different destinations. Rent subsidies in megacities primarily increase migration among advantaged individuals than disadvantaged ones, thereby exacerbating income disparities. Conversely, policies targeting disadvantaged groups or offering non-targeted subsidies in non-megacities help increase migration for disadvantaged people and increase intergenerational mobility.

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1 Introduction

Moving to wealthier regions has long been a critical pathway to improving one's economic prospects. China is a stark example where millions have moved from rural to urban areas to break the cycle of poverty. However, in China, as in many countries including the United States, housing prices have risen rapidly in high-income areas with abundant job opportunities. These rising housing costs may differentially affect the migration decisions of individuals from more or less advantaged backgrounds. This, in turn, may reinforce existing inequalities and decrease intergenerational mobility.

In this paper, using an instrumental variable approach that exploits the disparate impact of a government housing policy, I find that higher housing costs disproportionately deter migration among adult children of less-educated fathers, even after accounting for the child's own educational attainment. This heterogeneous impact leads to lower earnings for these individuals compared to those with more educated fathers, thereby reducing economic mobility across generations.

To further understand the heterogeneous impacts and explore the effects of various housing policies, I employ a structural approach. The analysis reveals a more nuanced pattern: while rising housing prices reduce migration overall, the heterogeneous impact of housing costs across parental backgrounds varies depending on the destination prefecture (the Chinese equivalent of a Metropolitan Statistical Area in the U.S.). High housing costs in Tier-1 prefectures (Beijing, Shanghai, Shenzhen, and Guangzhou) mainly deter migration among adult children of highly educated fathers. In contrast, for non-Tier-1 prefectures, the negative impact is larger for children of less-educated fathers. These findings suggest that to promote intergenerational mobility, policies should either target disadvantaged workers or reduce housing costs in non-Tier-1 prefectures. My policy experiments reinforce this conclusion.

Although there is an extensive literature on intergenerational mobility, its determinants, particularly in developing countries, remain unclear (Genicot et al., 2024). Most studies focus on correlations, with few investigating causal factors. This paper provides causal evidence that rising housing prices impede intergenerational mobility. This finding is particularly relevant in light of the recent surge in housing prices in both developing and developed countries such as India and the United States (Mahadevia et al., 2012; Ganong and Shoag, 2017).[1]

It is ex-ante ambiguous whether adult children from more or less advantaged back-

[1]See, e.g., "House prices continue to go through the roof" https://www.economist.com/graphic-detail/2021/08/12/house-prices-continue-to-go-through-the-roof and "Is your rent ever going to fall?" https://www.economist.com/international/2024/05/29/is-your-rent-ever-going-to-fall, etc.

grounds are more responsive to housing price changes. High housing costs may disproportionately limit migration for children from disadvantaged backgrounds, who often face credit constraints (see, e.g., Cai, 2020), compared to their more affluent peers, thereby reinforcing existing disparities. Conversely, housing price changes may affect affluent children more, as disadvantaged children are often too far from affording migration for small cost changes to matter. In contrast, children from wealthier families, being closer to the decision threshold, can be more sensitive to price fluctuations.

The effect of housing prices on migration decisions across different parental backgrounds determines how housing prices shape the transmission of socioeconomic status across generations. In other words, the impact of housing prices on intergenerational mobility is also theoretically unclear. To clarify the conditions under which housing prices may either facilitate or hinder intergenerational mobility through their effect on migration, I develop a theoretical model. The empirical analysis then reveals which effect dominates in the data and for which destinations.

I use China as a testing ground to examine how housing price shocks influence internal migration and intergenerational mobility. China offers a unique setting for several reasons. First, housing prices vary substantially across Chinese prefectures, providing rich variation to analyze its effects. Most importantly, the central government's Housing Purchase Restriction policy implemented in selected prefectures offers a natural experiment to identify the causal impact of housing price shocks. Second, the country has experienced rapid housing price appreciation over the past few decades (Fang et al., 2016), highlighting the significant impact of real estate fluctuations. Housing affordability has become a critical issue for migrants, who complain that "We have no home where there is work, and no work where there is home." Finally, China's high return to migration is well-documented, especially for workers from rural areas (see, e.g., Lagakos et al., 2020).

In the empirical analysis, housing costs are captured by the housing price gap, defined as the difference between the average-weighted housing prices across potential destinations and the housing price at the origin. The weights for each destination are derived from pre-existing migration patterns. For example, if more migrants from this origin moved to Shanghai than to Beijing, housing prices in Shanghai are assigned a larger weight than those in Beijing for this origin. Since migration is measured using cross-sectional data, capturing individuals' migration status at a single point in time, I calculate a weighted average of housing prices throughout their lives. The time series of housing price gaps are weighted according to their relevance in migration decisions, with greater emphasis placed on ages when migration is more prevalent, such as the 20s and 30s.

As housing prices are correlated with economic conditions, the OLS results are subject to omitted variable bias. For instance, fathers with higher education levels may be more effective at leveraging their social networks to secure job opportunities for their children in high-salary destination prefectures. Therefore, the coefficients might reflect fathers' differential capacity to facilitate their children's access to employment rather than the heterogeneous impacts of housing prices.

To address this concern, I exploit the Housing Purchase Restriction policy introduced in China around 2010 as a natural experiment to construct instrumental variables for housing prices. By restricting the number of properties that each household or firm could purchase, this policy led to an immediate and sharp decrease in housing demand. Since the policy was launched in only 46 prefectures, its impact can be assessed by analyzing outcome variation before and after the policy's implementation across both the affected and unaffected prefectures. This policy has been widely used as an unexpected shock to housing prices (Chen et al., 2017; Zhao and Zhang, 2022; Liu et al., 2023; Chen et al., 2023).

For parental socioeconomic status, I use fathers' education as a proxy.[2] I find that higher housing costs reduce migration, with the effect being less pronounced for individuals whose fathers have higher education levels. Similarly, higher housing costs lead to lower incomes, but this negative impact is again mitigated for those with more educated fathers. These results indicate that, as housing costs rise, the influence of parental background on children's income becomes more pronounced. In other words, higher housing costs lead to a decline in intergenerational mobility.

Heterogeneity analyses show that the basic education of the parents is most important for overcoming housing cost barriers. Beyond that, higher levels of education provide little additional advantages. Further examination reveals that the effects concentrate on children with rural parents, indicating that housing cost barriers primarily influence rural-to-urban migration. Since rural-urban migration is often linked to the transition from agricultural to non-agricultural employment, this finding suggests that housing prices impact agricultural employment differently depending on parental background, which is confirmed by the data. This finding highlights the interaction between housing costs, structural transformation, and intergenerational mobility.

I then use a more structural approach to analyze the policy implications, starting with a discrete choice model. While the reduced-form analyses treat migration as a binary

[2]There may be concerns that fathers' education may not be a good proxy for income, especially in rural areas. However, data show a strong correlation between education and both current income and household assets for the birth cohort of the sample's fathers, indicating that fathers' education is a valid proxy for income. I also replace fathers' education with imputed fathers' income and household assets for robustness checks.

decision—whether to migrate or not—the discrete choice model frames migration as a selection among multiple destinations. The analysis confirms that high housing costs reduce a prefecture's attractiveness, with the impact varying by fathers' education. Further examination shows that the different migration responses across parental backgrounds depend on the destination type: workers with low-education fathers are more responsive to housing price changes in non-Tier-1 prefectures, while those with high-education fathers are more sensitive to price changes in Tier-1 cities. This is because the costs of migration to megacities are so high that many disadvantaged children are so far from being able to afford it that small reductions in housing costs are insufficient to change their decisions. In contrast, children from wealthier families are more likely to be at the margin of making Tier-1 migration decisions and, thus, are more responsive to housing price fluctuations. This pattern emphasizes the need for policy design to account for the nature of the destination prefectures.

While the discrete choice model provides clear insights into migration responses to housing price changes, it does not account for the general equilibrium effect, through which changes in population size lead to subsequent adjustments in housing prices, which in turn influence migration until a new equilibrium is reached. I thus construct a full spatial equilibrium framework to account for the housing market responses and evaluate potential policies. I explore three types of rent subsidy policies: a non-targeted subsidy in Tier-1 prefectures, a targeted subsidy in Tier-1 prefectures for workers from disadvantaged families, and a non-targeted subsidy in non-Tier-1 prefectures. The findings suggest that to encourage migration among disadvantaged workers, policies should either directly target these workers in Tier-1 prefectures or focus on non-Tier-1 prefectures.

Using counterfactual simulations, in addition to analyses of migration responses, I provide back-of-the-envelope calculations of the impacts of different policies on intergenerational mobility and agricultural employment. The results suggest that to improve intergenerational mobility, a targeted rent subsidy in Tier-1 prefectures for disadvantaged migrants is most effective. Both targeted subsidies in Tier-1 prefectures and non-targeted subsidies in non-Tier-1 prefectures are similarly effective in reducing agricultural employment.

2 Relation to the Literature

First, this paper contributes to the literature on the barriers to internal migration. Previous research has identified various factors, including specific barriers such as the *Hukou* registration system[3] and the land tenure system, alongside broader issues like credit constraints, imperfect information, friction in job matching, risk aversion, transportation costs, and social constraints (see, for example, Zhao, 1999; Bryan et al., 2014; Angelucci, 2015; Munshi and Rosenzweig, 2016; Bazzi, 2017; Chen et al., 2018; Khanna et al., 2021; Morten and Oliveira, 2024). Related to the impact of housing costs on migration, Garriga et al. (2023) build a dynamic spatial equilibrium model to explore the interaction between structural transformation and the housing market, finding that rising house prices hinder migration. In the U.S., Ganong and Shoag (2017) document the lower migration rates of low-skilled workers to high-cost housing areas. This paper demonstrates that the effects of housing affordability on migration vary by parental background, impacting intergenerational mobility. The results also imply interactions between housing costs, intergenerational mobility, and structural transformation.

My work is closely related to two papers. Cai (2020) shows that increased credit access boosts migration in China, particularly in low-asset villages, and Bazzi (2017) finds that transient positive agricultural income shocks increase emigration, especially in villages with smaller landholders, while persistent income shocks reduce emigration in more developed regions, highlighting the role of wealth heterogeneity. While the two papers focus on village-level wealth measures, this paper explicitly analyzes the heterogeneous impacts based on individual-level parental backgrounds and examines the effects on intergenerational mobility. Moreover, I propose a new type of heterogeneity across household wealth, demonstrating through model and counterfactual analyses that wealthier households may respond more to reduced migration barriers—a finding not covered in previous literature and with important policy implications.

Secondly, my paper speaks to the literature on the determinants of intergenerational mobility (IGM). While intergenerational persistence is well-documented, the factors causally driving it are not fully understood. Previous studies highlight the importance of economic shocks, access to education, and segregation (for example, Parman, 2011; Feigenbaum, 2015; Chyn et al., 2022; Biasi, 2023; Kaila et al., 2025). Moreover, although there is extensive literature on IGM in developing countries, most research on the causal determinants of IGM focuses on developed countries (Genicot et al., 2024). This paper proposes housing prices as a new determinant, working through the channel of migration, and examines a developing context where geographic inequality and migration are critical in shaping social mobility.

Close to this study, Ward (2022) provides evidence that migration enhances intergen-

[3]The *Hukou* system in China functions as a domestic "passport system". It restricts internal migration by limiting access to social services such as education, healthcare, and housing subsidies in areas outside an individual's registered location.

erational mobility, especially noting its effectiveness for individuals from lower-income families. This paper complements this work by examining a distinct setting and focusing on the impact of elevated housing prices, a trend recently witnessed in many countries.

Finally, this paper contributes to the growing literature on the causal relationship between childhood exposure to better neighborhoods and intergenerational mobility. A series of studies have examined the impacts of the Moving to Opportunity (MTO) experiment (e.g. Chetty and Hendren, 2018). Similarly, Alesina et al. (2021) find that in Africa, spending an additional year in a high-mobility region between ages 5 and 12 significantly increases the likelihood of children from uneducated families completing primary school. This study, however, focuses on policies aimed at enhancing intergenerational mobility by encouraging migration in adulthood. This distinction highlights the different life stages—childhood versus adulthood—where targeted interventions can break the cycle of poverty and dependence on parental backgrounds.

3 Background

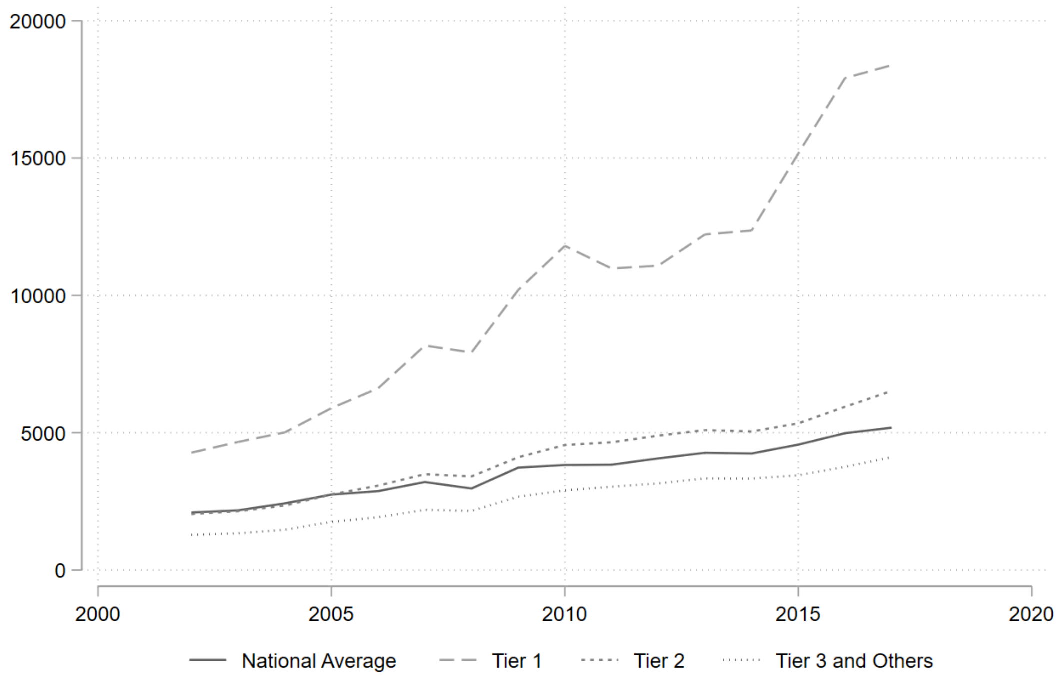
3.1 Housing Boom in China

The 1998 reform, which privatized the housing sector, initiated rapid growth of the real estate markets in China. As shown in Figure 1, housing prices in China have surged dramatically over the past two decades. Between 2002 and 2017, real housing prices in Tier-1 prefectures increased by 4.3 times, and those in Tier-2 prefectures rose by 3.2 times. Even after accounting for housing quality, from 2002 to 2013, the average yearly growth rate of residential housing prices in 35 major Chinese prefectures was 11.4 percent (Sun and Zhang, 2020). Such increases have been attributed to factors such as land supply restrictions, increases in mortgage supply due to fiscal stimulus, expected economic growth, etc. (see, for example, Wang and Wen, 2012; Fang et al., 2016; Sun and Zhang, 2020).

In tandem with the rise in housing prices, rental costs also surged, a factor of particular concern to migrants. According to data from the China Migrants Dynamic Monitoring Survey (CMDS), the median monthly rent in Tier 1 prefectures doubled from 500 RMB in 2011 to 1000 RMB in 2017, not taking into account the potential decrease in residential quality that migrants might accept to manage higher costs. After adjusting for the Consumer Price Index (CPI), this rise translates to a jump from 403 to 717 in 2000 RMB.

Despite the overall upward trend in housing prices over the past few decades, there are significant temporal and regional disparities across prefectures. This variation

Figure 1: Residential Housing Prices by Prefecture Tier (yuan/sq.m, 2000 RMB)



NOTE: This figure shows the CPI-adjusted annual housing prices across prefectures of different tiers from 2002 to 2017. Adjusting for CPI has minimal effect on the overall trend. Tier-1 prefectures consist of Beijing, Shanghai, Guangzhou, and Shenzhen. Thirty-one prefectures are classified as Tier-2. The remaining prefectures fall into Tier-3. Between 2002 and 2017, real housing prices in Tier-1 prefectures increased by 4.3 times, and those in Tier-2 prefectures rose by 3.2 times.
SOURCE: Rogoff and Yang (2020)

can be attributed to factors such as the differential housing supply elasticity, diverse local house purchasing policies, and spatial inequality in economic development (Saiz, 2010; Gyourko et al., 2022). Appendix Figure B.1 illustrates this variation by showing the residualized housing prices, which are derived from regressing housing prices on prefecture fixed effects and year fixed effects.

3.2 Housing Purchase Restriction Policy

On April 17, 2010, the State Council of China released the "Notice of the State Council on Resolutely Curbing the Excessive Rise of House Prices in Some Prefectures" aimed at moderating the surging housing prices in some urban regions. After this notice, Beijing pioneered the implementation of a Housing Purchase Restriction (HPR) policy on May 1, which limited households to buying no more than one new property. Subsequently, this policy was extended to an additional 45 major prefectures across China from late 2010 to early 2011, as detailed in Table B.2 (dates are from Chen et al. (2017)). While the specific regulations varied among these prefectures, the general framework of the HPR policy typically restricted Chinese households to owning no more than two properties, with a mandatory two-year interval between purchases. The policy was in place until 2014, after which it began to be slowly removed.

The policy was adopted abruptly and unexpectedly. Immediately following the implementation of the HPR policy, housing demand declined noticeably, leading to slower price growth and a reduction in the number of houses sold in the affected prefectures (Du and Zhang, 2015; Li et al., 2017). This paper utilizes this slowdown in the housing market, which affects migrants' housing affordability and, thus, their migration decisions.

4 Model

How do housing prices affect migration decisions and intergenerational mobility? To explore the relevant factors, I construct a model. The model outlines the conditions under which individuals from less privileged or more privileged families exhibit greater responsiveness to changes in housing prices. It also identifies when fluctuations in housing prices lead to either an increase or a decrease in intergenerational mobility.

In this section, I describe a discrete version of the model where the adult children's incomes are binary. A continuous version can be found in Appendix Section A, with similar main results.

Assume fathers' socioeconomic status, F, is high (H) or low (L). If the adult child stays, their income is Y^S, and if they migrate, their income is Y^M. $Y^M > Y^S$, meaning that migration increases income. I assume that all children are homogeneous, with migration status being the only factor influencing their income. Implicitly, I have already conditioned on, for example, education so that the effect of fathers on their children's education is removed. The father's type impacts children's income only through its effect on their migration status.

Migration incurs a monetary cost, denoted as $M(h, F)$, which depends on the housing cost h and the father's type F. Assume that $\frac{\partial M(h,F)}{\partial h} > 0$, meaning that an increase in housing costs increases migration costs. In addition to monetary costs, individuals experience psychological disutility associated with migration, denoted by τ. This disutility, τ, is independent of the father's type and the children's income. The cumulative distribution function (CDF) and probability density function (PDF) for τ are denoted as $G_\tau(\tau)$ and $g_\tau(\tau)$, respectively.

Combining the above benefits and costs of migration, a child will migrate if:

$$Y^M - Y^S - M(h, F) > \tau \tag{1}$$

where F represents either H or L.

Denote the left-hand side as $B(h, F)$, which is the net benefit of migrating. For a child faced with father's type F and housing cost h, the probability that they migrate is $Pr(migrate|h, F) = Pr(B(h, F) > \tau) = G_\tau(B(h, F))$.

In the empirical analyses, I regress the indicator for migration on the interaction term between paternal backgrounds and housing costs. As father's type is binary in the model, the sign of the interaction term corresponds to the sign of $\left(\frac{\partial Pr(migrate|h,F)}{\partial h}\Big|_{F=H} - \frac{\partial Pr(migrate|h,F)}{\partial h}\Big|_{F=L} \right)$. It can be derived that:

$$\frac{\partial Pr(migrate|h, F)}{\partial h} = -g_\tau(B(h, F))M'_F(h) < 0 \tag{2}$$

and

$$\frac{\partial Pr(migrate \mid h, F)}{\partial h}\Big|_{F=H} > \frac{\partial Pr(migrate \mid h, F)}{\partial h}\Big|_{F=L} \iff \frac{M'_H(h)}{M'_L(h)} < \frac{g_\tau(B_L)}{g_\tau(B_H)} \tag{3}$$

where B_F denotes $B(h, F)$, $M'_F(h)$ denotes $\frac{\partial M(h,F)}{\partial h}$ which is positive, and $F = H$ or L.

Equation (3) suggests that the impact of housing prices on migration decisions depends on two factors: the heterogeneous costs, $\frac{M'_H(h)}{M'_L(h)}$, and the different position at the disutility distribution, $\frac{g_\tau(B_L)}{g_\tau(B_H)}$. First, for the magnitude of $\frac{M'_H(h)}{M'_L(h)}$, I assume that increases in housing costs raise migration costs more for children with low-type fathers than for those with high-type fathers, i.e., $M'_H(h) < M'_L(h)$, due to restrictions faced by disadvantaged families, such as credit constraints. For $\frac{g_\tau(B_L)}{g_\tau(B_H)}$, $g_\tau(B_F)$ represents the sensitivity of disutility to the net benefit of migration. In the population, $\frac{g_\tau(B_L)}{g_\tau(B_H)}$ measures the relative number of children at the margin of deciding whether to migrate. If more children with high-type fathers are at the margin compared to those with low-type fathers, $g_\tau(B_H)$ is larger than $g_\tau(B_L)$, and vice versa.

In the empirical analysis, I also examine the effects of housing costs on children's income. According to the model, the expected income of children, regardless of migration status, is given by:

$$\begin{aligned} E[Y|h, F] &= G_\tau(B(h, F))Y^M + [1 - G_\tau(B(h, F))]Y^S \\ &= G_\tau(B(h, F))(Y^M - Y^S) + Y^S \end{aligned} \tag{4}$$

The impact of housing costs on income is:

$$\frac{\partial E[Y|h,F]}{\partial h} = -g_\tau(B(h,F))M'_F(h)(Y^M - Y^S) < 0 \tag{5}$$

I regress children's income on the interaction term between parental backgrounds and housing costs. The sign of the interaction term corresponds to the sign of $\left(\frac{\partial E[Y|h,F]}{\partial h}\Big|_{F=H} - \frac{\partial E[Y|h,F]}{\partial h}\Big|_{F=L}\right)$. It can be derived that:

$$\frac{\partial E[Y|h,F]}{\partial h}\Bigg|_{F=H} > \frac{\partial E[Y|h,F]}{\partial h}\Bigg|_{F=L} \iff \frac{M'_H(h)}{M'_L(h)} < \frac{g_\tau(B_L)}{g_\tau(B_H)} \tag{6}$$

which is the same condition as in Equation (3).[4]

Equation (6) suggests that the two mechanisms described above for Equation (3) on migration decision—heterogeneous migration costs and the relative number of people at the margin—also apply to the analysis of the heterogeneous impacts of housing costs on children's income. Furthermore, this equation has implications for the impact of housing costs on intergenerational mobility. I assume that children with high-type fathers have a higher average income compared to those with low-type fathers. If Equation (6) holds with its current direction, an increase in housing prices leads to a reduction in the average income of children, with a more pronounced decline for those with low-type fathers. This implies that rising housing prices widen the income gap between children of high- and low-type fathers, thereby reducing intergenerational mobility.

Overall, the impact of housing costs on migration decisions and children's income varies based on parental background. Whether the impacts are larger for children with high- or low-type fathers is theoretically ambiguous. Empirical analysis is crucial to identify the dominant factors in the data.

5 Data

I mainly use two sets of data: one on housing prices and one on workers.

[4]The model can be revised to reflect that, aside from migration status, the income of children also directly depends on the type of fathers. Data provides suggestive evidence that migration is more beneficial for children with low-type fathers, though not causal. Allowing for such dependency of children's income on father's type, $\frac{\partial E[Y|h,F]}{\partial h}\Big|_{F=H} > \frac{\partial E[Y|h,F]}{\partial h}\Big|_{F=L}$ would then be a necessary condition of $\frac{\partial Pr(migrate|h,F)}{\partial h}\Big|_{F=H} > \frac{\partial Pr(migrate|h,F)}{\partial h}\Big|_{F=L}$. The underlying idea is that children from low-income backgrounds benefit more from migration, but their migration decisions are also more sensitive to increases in housing costs, leading to greater negative impacts on their income when housing costs increase. The continuous version of the model in Appendix Section A incorporates this additional element.

5.1 Housing Prices and Local Economic Conditions

The panel data on housing prices are obtained from the CEIC database[5], which provides annual selling prices for residential properties in each prefecture. As the individual level data is in 2017, the housing price data used covers the period from 2000 to 2017. Housing price is measured in log yuan per square meter and adjusted to 2000 RMB using the national Consumer Price Index (CPI).

I use housing prices as a proxy for housing costs faced by migrants. Migrants typically do not purchase homes at their destinations due to both *Hukou* restrictions and liquidity constraints. According to the CMDS dataset, only 10-20% of migrants who move across prefectures purchase a house at their destination. What influences the migration decision more is the rental prices at the destination. Unfortunately, rental price data is limited in the Chinese context. Data suggests a strong correlation between rental prices and housing purchase prices: using rent data from Wind,[6] the correlation coefficient between log rent and log housing prices is 0.89. Therefore, I use housing prices as a proxy for the residential costs faced by migrants.[7]

The CEIC database also provides data on local economic conditions, including employment, wage, GDP per capita, exports, FDI, and fiscal expenditures.

5.2 Individual Characteristics

Individual characteristics are sourced from the China Household Finance Survey (CHFS), a nearly nationally representative survey project executed by the Research Center for China Household Finance.[8] The CHFS dataset provides a comprehensive and detailed description of household economic and financial behaviors. Further information about the dataset can be found in Gan et al. (2014).

This study uses data from the 2017 CHFS. I construct a sample where interviewees are treated as adult children and use their self-reported income and parental information for analysis. The sample includes both men and women. In addition to respondents' migration history, the CHFS provides detailed income data, including from the informal

[5]CEIC is a widely used macroeconomic database offering access to over 6.6 million time series across more than 200 economies. For more details, please refer to https://www.ceicdata.com/en.

[6]Wind is a Chinese financial data and software company based in Shanghai. It offers the Wind Financial Terminal, the leading domestic alternative to the Bloomberg Terminal in China. Wind's data is widely cited in authoritative Chinese and English media, research reports, and academic papers. For more details, please refer to https://www.wind.com.cn/.

[7]There may be concerns that many migrants live in poor conditions, potentially making their rent less sensitive to housing prices at their destination. However, CMDS data shows that rents paid by migrants across different percentiles (5th, 10th, ..., 95th) are all highly correlated with local housing prices.

[8]Tibet and Xinjiang are not included in the dataset. Together, they account for less than 2% of China's population, according to the National Bureau of Statistics.

sector and farming, which helps mitigate selection biases that commonly arise in studies lacking income data for workers in these sectors. The CHFS also collects basic parental information, such as education and *Hukou* status, regardless of whether parents co-reside with the respondent or are still alive, reducing selection bias typically seen in studies focused only on cohabiting household members.

I restrict the sample as follows: First, since migration behavior may differ for workers from megacities, I exclude observations whose origin is Tier-1 prefectures (Beijing, Shanghai, Shenzhen, and Guangzhou). Second, I limit the sample to individuals aged 17-55. The results are not sensitive to changes in the age range. Appendix Table B.3 shows the descriptive statistics.

5.3 Other Datasets

I also use census sample data from 2000, 2005, and 2010, as well as the China Migrants Dynamic Monitoring Survey (CMDS) from 2010 to 2017, for the construction of some variable and relevant statistics, which I explain in detail as they arise.

6 Empirical Approach

I begin the analyses by exploring how housing prices influence migration decisions and income, with a focus on how these effects vary by fathers' years of education. To address potential endogeneity concerns regarding housing prices, I employ a 2SLS estimation, using the HPR policy to construct the instrumental variable.

Aligning with the simple model of one origin and one destination, this analysis does not differentiate between specific destinations; instead, I average housing price gaps across all potential destinations. In later sections, I account for variation across different destinations.

6.1 Baseline

I run the following regression to examine the heterogeneous impacts of housing prices on migration and income across different parental backgrounds. For adult children i born in year t whose origin is prefecture o, I estimate the following equation:

$$\begin{aligned} Outcome_{iot} = \beta_1 FatherEduy_{iot} \times HPgap_{ot} + \beta_2 FatherEduy_{iot} \\ + \beta_3 HPgap_{ot} + \Pi Z_{ot} + \Omega X_{iot} + \mu_t + \eta_o + \epsilon_{iot} \end{aligned} \tag{7}$$

where β_1 is the coefficient of interest. $Outcome_{iot}$ is either the indicator for migration or log income. Migration is defined as residing in a prefecture different from one's origin, where the origin is defined as the prefecture in which the individual lived at age 14. Results are robust using other ages such as 16 and 18. $HPgap_{ot}$ measures the housing price gap between the origin and potential destinations, which I will describe in detail below. Note that the time dimension is based on birth year rather than calendar year, as I account for an individual's life cycle, weighting each age according to its importance for migration decision-making. $FatherEduy_{iot}$ denotes the individual's father's years of education. The individual-level control variables, X_{iot}, include gender, parents' *Hukou* status, and education fixed effects. The origin-by-birth year level controls, Z_{ot}, include log wage levels, employment, and exports at the origin prefecture, as well as weighted averages of log wage levels, employment, and exports at the destination prefectures.[9] μ_t and η_o represent fixed effects for birth year and origin prefecture, respectively.

Given the persistent rise in housing prices in China over recent decades, there is concern that $FatherEduy \times HPgap$ may largely reflect cohort-specific effects of fathers' education. For example, in many prefectures, $HPgap$ has been increasing over time, which could confound the results if the influence of fathers' education on children's outcomes is also growing for reasons unrelated to housing price changes. To address this, I control for the interaction between fathers' education and birth year fixed effects, allowing the impact of fathers' education to vary across birth cohorts. This approach isolates the time-varying effects of education, thereby refining the estimate of β_1.

Although I use cross-sectional data from a single year, the survey provides information on migration history, including origin, destination, and year of migration, allowing me to infer housing prices during working ages. Ideally, each migration decision would be matched with housing market characteristics at the time when the individual was contemplating whether to migrate. In practice, following Sun and Zhang (2020), the expected housing price gap the individuals were exposed to is calculated as follows. The expected housing price gap each individual was exposed to is defined as the price difference between the origin and potential migration destinations, weighted by the importance of each destination for that origin. The time series of the gap is then averaged, with weights based on the significance of each year during critical ages when migration decisions are made in the individual's life cycle.

To construct the expected housing price gap, first, using China's 2010 census sample, I calculate the age-specific migration probability, defined as the proportion of individuals

[9]For the reduced-form results, macroeconomic controls are included for migration outcomes to address potential omitted variable bias but are excluded from the income outcomes to avoid issues related to bad controls. The results remain robust regardless of whether macroeconomic controls are included or not for both outcome variables. A detailed discussion of this issue can be found in Appendix Section C.

who migrated at age k relative to the total number of migrants.

$$a_k = \frac{\# \, of \; migrants \; migrated \; at \; age \; k}{\# \, of \; migrants}$$

Appendix Figure B.3 shows the plot of the age-specific migration probability. The figure suggests that most workers migrate in their 20s or 30s when they are young adults—old enough to migrate independently but still young enough to receive parental support. While I assume the age-specific migration rate is homogeneous across regions, the results remain robust when using province-specific rates. The analysis using rates calculated from the 2000 and 2005 census data yields similar results.

With the age-specific migration probability, I can construct the expected housing price gap. To minimize the influence of parental migration decisions, the calculation begins at age 16; it ends at age 45, as data indicates minimal migration occurs after that age. Adjusting these thresholds yields similar results. If the individual is under 45 years old, they were exposed no later than their current age, so the sum extends only up to their current age. For an individual born in year t, at age l, originating from prefecture o, the expected housing price gap to which they were exposed is defined by the following expression:

$$HPgap_{ot} = \frac{\sum_{k=16}^{min\{l,45\}} a_k \times (lnprice\_dest_{o,t+k} - lnprice_{o,t+k})}{\sum_{k=16}^{min\{l,45\}} a_k}$$

Where $lnprice_{o,t+k}$ is the log housing price in the origin prefecture o in year $(t+k)$, and $lnprice\_dest_{o,t+k}$ is the weighted average housing price at potential destinations for the same year. For transparency and to address concerns about functional form, the results remain robust when using the housing price gap at a specific age, such as 20. This is unsurprising because most moves occur within a small age range during which relative price changes are modest.

To calculate the weighted average housing prices of potential destinations, I use Census 2000 data to generate weights based on migration patterns prior to the sample period. The proportion of migrants from a given origin moving to each specific destination serves as the weight. For instance, if 50% of migrants from prefecture o moved to Shanghai, Shanghai's housing price is given a 50% weight in the calculation for prefecture o. The formula is as follows:

$$lnprice\_dest_{ot} = \sum_d w_{od} lnprice_{dt}$$

where w_{od} is the fraction of migrants from origin prefecture o who migrated to prefecture d, and $\sum_d w_{od} = 1$. Alternatively, I replace migration pattern weights with the ratio of the destination prefecture's 1999 GDP to the distance from the origin, following the concept of market access as in Donaldson and Hornbeck (2016). The results remain robust.[10] Appendix Table B.1 provides a simple numerical example of how the housing price gap measure is constructed.

Control variables at the origin-by-birth-year level are weighted similarly. For example, the log wage at the origin is calculated as a weighted average based on age-specific migration probabilities. Destination wages are also weighted, first by migration patterns and then by age-specific migration probabilities.

6.2 Instrumental Variable

Housing prices are highly correlated with local economic conditions. To address the endogeneity issue, an instrumental variable is needed to capture the impacts of housing prices. The HPR policy is leveraged as a natural experiment to construct the instrumental variable.

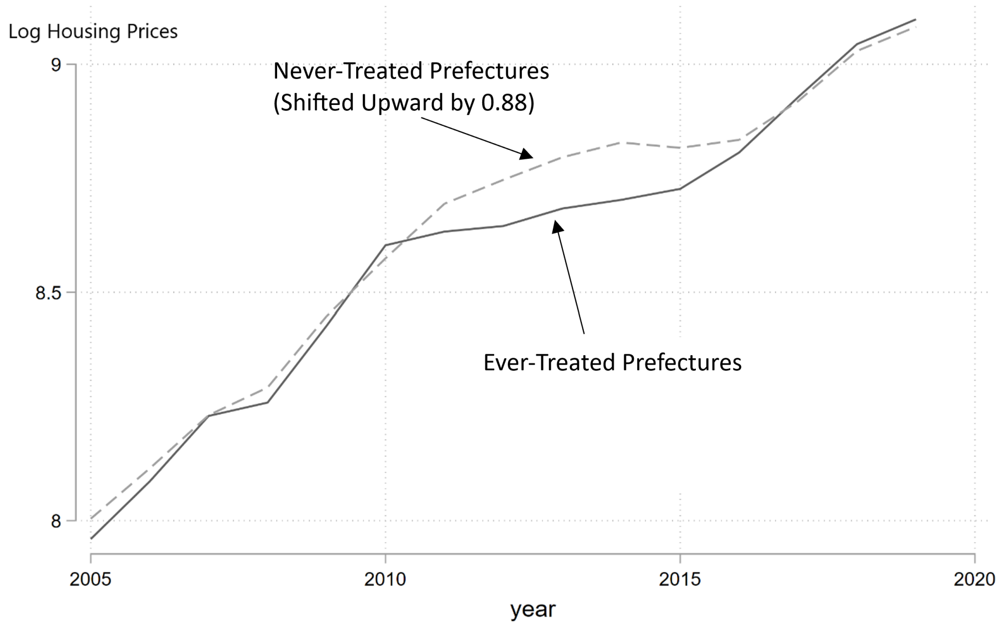
Figure 2 shows the housing prices time series between the prefectures that ever implemented the HPR policy and those that never did, measured in log yuan per square meter, adjusted to 2000 RMB. To facilitate comparison, housing prices in the never-treated prefectures are shifted upward by 0.88 log points. Visually, the pre-trend appears parallel before the implementation of the HPR policy around 2010. Since the implementation of the policy, the growth of the treated prefectures immediately slowed, while the housing prices in untreated prefectures kept growing. As the treated prefectures gradually relaxed the restriction in 2014-2016, the differences returned to the original level.

Appendix Figure B.2 shows the event study plot for the policy. The estimates indicate that the gap in log housing prices between ever-treated and never-treated prefectures was stable before the policy, narrowed significantly during the policy, and returned to the original level after the policy was lifted in most treated prefectures.

To construct the instrumental variable, I first create a prefecture-year dummy indicating whether the HPR policy is in effect. These dummies for the origin and destination prefectures are then weighted and summed in the same manner as the housing price gaps. The resulting weighted average of the policy indicators, HPR_{ot}, serves as the instrumental variable for the housing price gap.

[10] Instead of using the weighted average of destination housing prices, I create individual-destination level observations to analyze the impact of housing prices at each specific destination on the likelihood of migrating there. The results remain qualitatively similar.

Figure 2: Housing Prices for Ever-Treated and Never-Treated Prefectures



NOTE: The figure shows the time series of housing prices between the prefectures that ever implemented the HPR policy and those that never adopted it, measured in log yuan per square meter, adjusted to 2000 RMB. For clearer comparison, the housing prices of the never-treated prefectures are shifted upward by 0.88 log points.

The instrumental variable is essentially a linear shift-share IV, where the shock is exogenous. Borusyak et al. (2022) has demonstrated the validity of this approach.[11]

7 Reduced-Form Results

I begin by examining the impact of housing costs on migration. I estimate Equation (7) using OLS, and the results are presented in Table 1, Column (1). The OLS estimates are subject to endogeneity issues, as unobserved factors such as job opportunities may confound the relationship between housing prices and migration. For example, regions with higher housing prices often have higher GDP, which attracts migrants, while higher housing costs discourage migration. This conflicting impact of GDP likely attenuates the negative effect of housing costs on migration. Consistent with this, the magnitudes of the OLS coefficients for housing price gaps are smaller than the IV estimates in Columns (2)-(4), reflecting omitted variable bias.

[11] As the shift-share instrumental variable in this paper is linear in the exogenous shocks, it is valid given that the origin fixed effects are controlled for. I further examine the robustness using the recentering approach following Borusyak and Hull (2023). The results remain robust.

Table 1: Main Results: Migration

	Migration			
	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)
FatherEduy	0.005***	0.005***		
	(0.001)	(0.001)		
FatherEduy× HPgap	0.009***	0.011***	0.011***	0.009***
	(0.001)	(0.002)	(0.002)	(0.002)
HPgap	-0.252***	-0.753***	-0.779**	-0.699**
	(0.073)	(0.292)	(0.303)	(0.297)
Eduy× HPgap	-	-	-	√
FatherEduy× birthyearFE	-	-	√	√
K-P F-stat		40.013	37.685	25.508
LM test		70.140	67.772	68.667
Obs.	14,976	14,976	14,976	14,976
Mean(Dep. Var.)	0.202	0.202	0.202	0.202

NOTE: This table shows the main results using the HPR policy to construct the instrumental variable. $FatherEduy$ is fathers' years of education, and $HPgap$ is housing price gap. In Columns (2) and (3), the endogenous variables are $HPgap$ and $FatherEduy \times HPgap$; the instrumental variables are HPR and $FatherEduy \times HPR$. In Column (4), the endogenous variables are $HPgap$, $FatherEduy \times HPgap$, and $Eduy \times HPgap$; the instrumental variables are HPR, $FatherEduy \times HPR$, and $Eduy \times HPR$. All columns include control variables. These controls include gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and education. Log wage, log employment, and log export at the origin prefecture, as well as the weighted averages of the log wage, log employment, and log export at the potential destination prefectures, are controlled in addition. The K-P F-stat row shows the F-stats of the first stages. The LM test row shows the statistics for the underidentification test. A rejection of the null indicates that the matrix of first-stage coefficients has full column rank, i.e., the model is identified. The results of the first stages are shown in Appendix Table B.4. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

Endogeneity can also affect the interaction term. For instance, fathers with higher education may better leverage social networks to help their children find employment in high-income prefectures. Consequently, the coefficients could capture fathers' differing abilities to facilitate employment for their children rather than the heterogeneous effects of housing prices. Given the endogeneity issues with the OLS estimates, the following analyses focus on the instrumental variables (IV) results.

Columns (2)-(4) show the results using the IV approach. Row "K-P F-stat" shows the first-stage *F-stats*, which are larger than 10, suggesting strong first stages. The "LM test" row presents statistics testing whether the matrix of first-stage coefficients has full column rank. High values indicate that the instruments provide sufficient independent variation to explain the endogenous variables. The results of the first stages are shown in Appendix Table B.4. The impacts of the HPR policy on housing costs are negative, as the HPR policy slows housing price growth.

To address the concerns that the interaction term between fathers' education and housing price gap, $FatherEduy \times HPgap$, may primarily capture heterogeneous impacts of fathers' education across birth cohorts, I include an interaction between fathers' education and birth year fixed effects. This allows the effect of fathers' education to vary by birth year, enabling me to focus solely on the heterogeneous impact of housing prices without the time-varying effect of fathers' education. The results are shown in Column (3), and the coefficients of interest barely change.

Because fathers' education affects children's education, one potential explanation for the findings is that fathers' education proxies children's education, and it is children's education that helps overcome housing cost barriers. While such a channel also suggests intergenerational persistence, the policy implications differ based on whether the focus is on enhancing educational opportunities or improving labor market access. To exclude the effect of children's education, I include the interaction term between the children's own education and the housing price gap, $Eduy \times HPgap$, in Column (4). The coefficients for $FatherEduy \times HPgap$ remain similar, indicating that fathers' education continues to help through channels other than children's education.

To interpret the coefficients, it's important first to understand the scale of the housing price gap. The housing price gap is a weighted average of the difference between the log housing prices at potential destinations and the origin. The mean of the housing price gap is 0.55, indicating that housing prices at the destinations are approximately 173% of those at the origin. Since both fathers' education and the housing price gap are demeaned, the magnitudes of the coefficients reflect the impacts at the mean housing price gap and mean fathers' education.

In Columns (2)-(4), the coefficients for the housing price gap, $HPgap$, are negative, indicating that higher housing costs reduce migration. In terms of magnitudes, the coefficient of -0.699 in Column (4) indicates that a 10-percentage-point increase in the housing price gap reduces migration by approximately 7 percentage points. This effect is about 35% of the mean migration rate and accounts for 56% of the average gap in migration rates between individuals with below-median and above-median education levels. The positive coefficient for the interaction term between fathers' years of education and the housing price gap, $FatherEduy \times HPgap$, suggests that fathers' education can mitigate the adverse effects of housing costs. However, this mitigation is insufficient to fully offset the housing cost barrier, which would require approximately 70 years of education, an unattainable amount. Note that, in Column (4), the results are conditional on the effects of children's own education on overcoming housing barriers, so the coefficients primarily reflect the impact of fathers' education rather than the characteristics of the children themselves.

The coefficients for the years of education of the father, $FatherEduy$, are positive, suggesting that children with fathers of higher education levels are more likely to migrate. Moreover, as the positive coefficients for the interaction term imply that fathers' education helps overcome the housing costs barrier, the impact of fathers' education on children's migration is more pronounced as housing price gaps increase. The coefficient for the interaction term in Column (4), which is 0.009, suggests that a 10-percentage-point increase in the housing price gap could raise the correlation between fathers' years of education and children's probability of migration from 0.005 (the coefficient for $FatherEduy$ in Column (1)) to 0.0059, reflecting an 18% increase in the importance of fathers' education on children's migration.[12]

Next, I examine the impacts on income, with the results presented in Table 2. The specifications mirror those in Table 1, but with the outcome variable replaced by log income. Column (1) shows the OLS estimates. Columns (2)-(4) show the results using the IV approach. Row "K-P F-stat" shows the first-stage *F-stats*, which are larger than 10, suggesting strong first stages. The sample sizes are smaller, as only observations with available income information are included.

The negative coefficients of $HPgap$ indicate that higher housing costs are associated with lower income. This aligns with expectations, as migration typically leads to income gains, and higher housing costs act as a barrier to migration. The positive and significant coefficients for the interaction term $FatherEduy \times HPgap$ suggest that higher levels of fathers' education mitigate, though do not fully offset, the adverse effects of housing costs on children's income.

The coefficient of $FatherEduy$ is positive and significant, suggesting that the ed-

[12]The 18% increase is calculated as .009×.1/.005=18% .

Table 2: Main Results: Income

	lnIncome			
	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)
FatherEduy	0.023***	0.023***		
	(0.004)	(0.004)		
FatherEduy× HPgap	0.028***	0.022**	0.021**	0.027***
	(0.006)	(0.010)	(0.009)	(0.010)
HPgap	-0.795**	-2.852**	-2.720**	-3.009**
	(0.334)	(1.288)	(1.327)	(1.351)
Eduy× HPgap	-	-	-	√
FatherEduy× birthyearFE	-	-	√	√
K-P F-stat		66.829	62.223	41.908
LM test		114.214	107.637	110.246
Obs.	12,068	12,068	12,068	12,068
Mean(Dep. Var.)	9.798	9.798	9.798	9.798

NOTE: This table shows the main results using the HPR policy to construct the instrumental variable. All columns include control variables. These controls include gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and education. The K-P F-stat row shows the F-stats of the first stages. The LM test row shows the statistics for the underidentification test. The results of the first stages are shown in Appendix Table B.4. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

ucation of fathers is positively correlated with the income of the children. The coefficient of fathers' education, 0.023, implies that an additional year of fathers' education increases adult children's income by 2.3 percentage points.[13] The coefficient for $FatherEduy \times HPgap$ in Column (8), which is 0.027, indicates that a 10-percentage-point increase in the housing price gap could raise the correlation between fathers' years of education and children's income from 0.023 (the coefficient for $FatherEduy$ in Column (5)) to 0.0257, representing a 12% increase in intergenerational persistence (IGP).[14] Using different benchmarks, the .0027 change caused by a 0.1 increase in the housing price gap is 38% of the standard deviation of IGP at the province level or 74% of the difference between the 50th and 75th percentiles.

[13] The magnitude is close to the findings in the literature. For example, Lee et al. (2024) find that an exogenous one-year increase in parents' schooling increases children's lifetime earnings by 1.2 percent on average. My estimates are somewhat larger.

[14] The 12% increase is calculated as $0.027 \times 0.1 / 0.023$.

7.1 Robustness

7.1.1 Measurement of Intergenerational Mobility

A large body of literature addresses the measurement of intergenerational mobility (IGM). The most common measures (of low IGM) include the intergenerational income elasticity (IGE), obtained by regressing children's log income on parents' log income, the intergenerational income correlation (IGC), and the rank-rank correlation, which regresses children's percentile rank on their parents' percentile rank (see, e.g., Genicot et al., 2024, for a survey of mobility measures). In this paper, I use the impact of fathers' education on children's income as a measure of intergenerational persistence, as fathers' education is reported best. Education is also less affected by transitory fluctuations and remains fixed once completed, unlike income, making it a common proxy for parental lifetime income (Solon, 1992; Gong et al., 2012). To address concerns like attenuation bias discussed in the literature, I conduct the following robustness checks.

First, since the data is cross-sectional, children's income is from the year 2017. Income data from a single year may be subject to transitory shocks or measurement errors. However, this is less concerning here since income is the dependent variable, not the independent variable, and the measurement error is likely classical. While classical measurement error in the dependent variable may add noise, it does not introduce bias. The independent variable, fathers' education, is stable and less prone to transitory shocks or measurement errors. To further address this concern, I follow Nybom and Stuhler (2017) and calculate average income across the 2015, 2017, and 2019 waves of the CHFS, provided income data are available. Appendix Table B.9 presents the results using multi-year average income. The estimated coefficients are similar between single-year and multi-year income measures.

Secondly, since my dataset includes children from various prefectures and birth years, the same level of fathers' education may represent different socioeconomic backgrounds. For example, a father with a high school education in a remote area may have a very different status compared to one in Beijing. To address this concern, I use residualized fathers' years of education, obtained by regressing fathers' education on *Hukou* status and origin-by-birth-year fixed effects. The results, shown in Appendix Table B.10, are similar to the main results in Table 1 and Table 2.

While education is an important indicator of parental background, it does not capture all aspects. Fathers with the same educational level may still have very different incomes and household wealth. To address this, I re-estimate the main results using imputed fathers' income or household wealth. I impute fathers' lifetime income based on parental education, *Hukou* status, Communist Party membership, job position, and coastal region indicators. These variables are relatively stable over the life cycle and correlate strongly with lifetime earnings, reducing lifecycle bias. Additionally, using estimated rather than actual income helps mitigate attenuation bias from temporary income fluctuations (Fan et al., 2021). The details of the imputation procedure are described in Appendix Section D.

Table 3: Robustness: Impute Fathers' Income

	(1) Migration	(2) Migration	(3) Migration	(4) lnIncome	(5) lnIncome	(6) lnIncome
lnFatherIncome	0.085***			0.381***		
	(0.013)			(0.059)		
lnFatherIncome× HPgap	0.162***	0.185***	0.138***	0.311*	0.355**	0.437***
	(0.036)	(0.034)	(0.037)	(0.167)	(0.150)	(0.165)
HPgap	-0.852***	-0.868***	-0.770***	-3.107**	-2.775**	-3.069**
	(0.294)	(0.304)	(0.297)	(1.267)	(1.299)	(1.330)
Eduy× HPgap	-	-	√	-	-	√
lnFatherIncome× birthyearFE	-	√	√	-	√	√
K-P F-stat	40.055	37.911	25.658	67.002	63.563	42.697
LM test	70.032	67.733	68.631	113.223	108.382	111.236
Obs.	14,955	14,955	14,955	12,051	12,051	12,051
Mean(Dep. Var.)	0.202	0.202	0.202	9.798	9.798	9.798

NOTE: This table shows the results using imputed fathers' income in place of fathers' education. All columns include control variables. These controls consist of gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and education. For Columns (1) - (3), log wage, employment, and exports at the origin prefecture, weighted averages of the log wage, employment, and exports at the potential destination prefectures are controlled in addition. The K-P F-stat row shows the F-stats of the first stages. The LM test row shows the statistics for the underidentification test. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

I re-estimate the main results using imputed fathers' income instead of fathers' education. Table 3 presents the findings. The F-statistics for the first stage remain above 10, indicating strong first-stage regressions. While the results follow similar patterns to the main table, the magnitudes differ due to the use of different measures of parental background. In terms of magnitude, estimates in Column (6) imply that a 10-percentage-point change in the housing price gap raises intergenerational persistence by 11%.

A similar procedure is applied to impute household assets. Appendix Table B.12 shows the results where fathers' education is replaced with imputed household assets. The results remain robust.

7.1.2 Additional Robustness Tests

The housing price gap is at the origin times birth year level, where the corresponding weights of the potential destinations are specific to each origin. There may be concerns that some unobservable economic conditions at the origin can confound the results. To address this concern, I include origin times birth year fixed effects, which would capture the time-variant characteristics in the origin and the origin-specific weighted averages of destination shocks. The results are shown in Appendix Table B.5. The estimated coefficients of interest remain close to the main results.

Recent econometric literature (Feigenberg et al., 2023) highlights that omitted variable bias may confound interaction terms, even when level terms of confounders are controlled. To address this, I control for the interaction between fathers' education and potential confounders. In Appendix Table B.5, I include the interactions between fathers' education and variables such as employment, wages, fiscal expenditure, exports, and FDI at both the origin and destination prefectures, along with the level terms for these economic conditions. The results remain similar to the main results.

A notable potential omitted variable is the price of non-housing goods. In Appendix Table B.6, I control for these prices and their interaction with fathers' education. The non-housing goods price data is obtained from the China Stock Market and Accounting Research (CSMAR) database. Including these additional controls does not affect the estimates of the key coefficient.

Characteristics of the origin prefecture may influence migration responses to housing price changes. For instance, individuals from economically developed or popular destination prefectures may exhibit different migration behaviors. To address this, I exclude from the sample the top ten prefectures by GDP per capita or the top ten most popular destinations, then rerun the main regressions.[15] Additionally, people born in prefectures adjacent to megacities such as Beijing or Shanghai may choose to live in their origin prefecture and commute rather than rent or purchase houses in the megacities. Another concern is that housing prices may have geographical spillovers, which could affect migrations through an income effect. To check whether these concerns matter for my result, I run the main regressions excluding the prefectures that are adjacent to the Tier-1 prefectures: Beijing, Shanghai, Shenzhen, or Guangzhou.[16] Appendix Table B.7 shows the results restricting the origin prefectures as described above. The results are close to the main findings.

The housing price data used in the main results comes from the CEIC database. To verify that the observed patterns are not specific to CEIC, I also use data from Anjuke,

[15] The top ten prefectures by GDP per capita in 2000 were Shenzhen, Shanghai, Zhuhai, Wuxi, Suzhou, Guangzhou, Beijing, Xiamen, Dongying, and Hangzhou. Aside from megacities like Beijing and Shanghai, the top ten vary across years. Using other years yields similar results. Based on 2010 census data, the top ten destinations are Beijing, Shanghai, Shenzhen, Guangzhou, Dongguan, Hangzhou, Suzhou, Chengdu, Ningbo, and Foshan.

[16] The adjacent prefectures are Baoding, Shaoguan, Suzhou, Zhongshan, Tianjin, Dongguan, Zhangjiakou, Chengde, Jiaxing, Qingyuan, Langfang, Foshan, Huizhou.

a leading online real estate platform in China which is known for its extensive listings and comprehensive services for property buying, selling, and renting. The results are shown in Appendix Table B.8. The estimates are close to the main results using the CEIC data, suggesting that I am not capturing dataset-specific patterns.

7.2 Heterogeneity Analysis

7.2.1 Fathers' Education Levels

This section explores the heterogeneous impacts across different subgroups. First, I analyze which level of education of fathers matters most in overcoming housing barriers.

Table 4 shows the results of interacting different levels of fathers' education with housing price gaps. Fathers' education is categorized into four levels: 1) no schooling (32.36% of the sample), 2) primary school (32.91%), 3) junior high school (19.21%), and 4) senior high or above (15.52%), with 'no schooling' as the reference group. To assess the incremental impact of each level, I use indicators for reaching or exceeding specific thresholds. For example, the coefficient of $1\{FatherEduLevel \geq 3\} \times HPgap$ reflects the added impact of a junior high education compared to primary school in overcoming housing barriers. A significant positive coefficient suggests an advantage from higher education, while an insignificant one indicates that further education beyond the previous level does not significantly help.

Columns (1) and (3) of Table 4 show the impacts on migration. The results reveal that, compared to fathers with no schooling, having a primary school education significantly helps overcome housing barriers, as indicated by the positive and statistically significant coefficients. The magnitudes of the coefficients of having a junior high school education are nonnegligible, although noisily estimated. Further education beyond junior high school, such as senior high school or higher, does not yield statistically significant additional benefits in mitigating the challenges posed by housing expenses. Columns (2) and (4) display the impacts on income, which are consistent with the migration findings, suggesting that the critical threshold for overcoming the adverse effects of housing prices on income lies at the middle school level. Later in the structural model, I use this threshold to split the data.

The findings imply that fathers with low education attainment are much less able to help their children overcome housing barriers, thereby limiting the children's opportunities for migration and economic advancement. These results align with the broader literature on poverty traps, which emphasizes how different constraints severely restrict people's ability to migrate, even within their own country. These findings underscore the importance of affordable housing policies, particularly for those at the bottom of

Table 4: Heterogeneity: Fathers' Education Levels

	OLS		IV	
	(1) Migration	(2) lnIncome	(3) Migration	(4) lnIncome
$1\{FatherEduLevel \geq 2\} \times$ HPgap	0.045***	0.130*	0.073***	0.205*
	(0.011)	(0.069)	(0.019)	(0.115)
$1\{FatherEduLevel \geq 3\} \times$ HPgap	0.027*	0.092	0.018	0.132
	(0.015)	(0.069)	(0.022)	(0.090)
$1\{FatherEduLevel \geq 4\} \times$ HPgap	-0.000	-0.020	0.009	-0.036
	(0.019)	(0.076)	(0.025)	(0.102)
HPgap	-0.297***	-0.811**	-0.668**	-2.863**
	(0.073)	(0.347)	(0.303)	(1.363)
FatherEduLevelFE× birthyearFE	√	√	√	√
K-P F-stat			14.462	23.837
LM test			65.974	108.881
Obs.	14,976	12,068	14,976	12,068
Mean(Dep. Var.)	0.202	9.798	0.202	9.798

NOTE: This table shows the IV results for heterogeneity across adult children with fathers of different education levels. The interaction term between the individual's education and the housing price gap is included in all columns. All columns include control variables. These controls consist of gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and education. For Columns (1) and (3), log wage, employment, and exports at the origin prefecture, weighted averages of the log wage, employment, and exports at the potential destination prefectures are controlled in addition. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

the income distribution, as such measures can greatly enhance economic mobility and reduce persistent poverty.

7.2.2 Rural vs Urban

I also examine heterogeneity between children from rural and urban areas. Children with at least one parent holding a rural *Hukou* are classified as from rural areas. I avoid using children's *Hukou* type directly, as it can be endogenous to migration behavior. Columns (1) and (2) of Table 5 present results for rural children, while Columns (3) and (4) show results for urban children. The findings indicate that parental background plays a significant role in helping rural children overcome housing cost barriers. In contrast, for urban children, the coefficients are smaller and not statistically significant, suggesting a negligible effect of parental education on housing barriers. The differences between the rural and urban groups in terms of the impacts on income are statistically significant, highlighting distinct impacts of housing cost barriers across the two groups.

Table 5: Heterogeneity: Rural vs Urban

	Rural		Urban	
	(1) Migration	(2) lnIncome	(3) Migration	(4) lnIncome
FatherEduy× HPgap	0.012***	0.044**	0.006	-0.013
	(0.003)	(0.014)	(0.004)	(0.014)
K-P F-stat	20.126	38.658	16.983	17.990
LM test	56.090	103.368	50.227	52.676
Obs.	10,081	8,303	4,895	3,765
Mean(Dep. Var.)	0.210	9.516	0.179	10.419

NOTE: This table shows the IV results for heterogeneity across adult children from rural versus urban areas. The interaction between fathers' years of education and birth year fixed effects and the interaction term between the individual's education and the housing price gap are included in all columns. All columns include control variables. These controls consist of gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and education. For Columns (1) and (3), log wage, employment, and exports at the origin prefecture, weighted averages of the log wage, employment, and exports at the potential destination prefectures are controlled in addition. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

These findings highlight the challenges rural families face and underscore the critical role of parental background in mitigating these barriers for workers from rural areas. Given that most rural workers migrate from rural to urban areas, the results suggest that rural-urban migration is the most affected by housing cost barriers compared to other types of migration.

7.3 Impacts on Structural Transformation

In the heterogeneity analysis, I find that housing costs have a greater impact on individuals from rural areas. Since rural workers' migration decisions are closely linked to the transition from agricultural to non-agricultural employment, housing prices can affect agricultural employment. When housing prices decrease, more workers migrate, and because migration is strongly associated with non-agricultural employment, the overall share of workers in agricultural employment declines across the entire population. This variation highlights a complex interaction between housing costs, structural transformation, and intergenerational mobility. To verify this, I examine the effects of housing costs on agricultural employment using the rural sample, irrespective of migration status.

Table 6 shows the results of this analysis, where the outcome variable is whether the individual works in the agricultural sector. The findings suggest that higher housing costs

Table 6: Impacts on Agricultural Employment

	Rural Sample	
	(1)	(2)
FatherEduy× HPgap	-0.006*	-0.008**
	(0.003)	(0.003)
HPgap	1.031*	1.105*
	(0.601)	(0.613)
Eduy× HPgap	-	√
K-P F-stat	30.197	20.063
LM test	56.791	56.562
Obs.	8,123	8,123
Mean(Dep. Var.)	0.293	0.293

NOTE: This table shows the results using agricultural employment as the outcome. The interaction between fathers' years of education and birth year fixed effects is included in all columns. All columns include control variables. These controls consist of gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and education, log wage, employment, and exports at the origin prefecture, weighted averages of the log wage, employment, and exports at the potential destination prefectures. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

increase the likelihood of working in the agricultural sector, as shown by the positive and significant coefficients for $HPgap$. Moreover, the interaction between fathers' education and housing costs reveals that higher levels of fathers' education mitigate the impact of housing costs on the probability of working in agriculture. The negative and significant coefficients for the interaction term $FatherEduy \times HPgap$ indicate that as fathers' education increases, the influence of housing costs on agricultural employment decreases. This suggests that families with more educated fathers are better equipped to navigate the challenges posed by housing costs, enabling their children to pursue non-agricultural employment opportunities.

The heterogeneous effects of housing costs on agricultural employment across different parental backgrounds highlight the role of housing costs in shaping structural transformation and social mobility. The findings suggest that housing costs may reinforce existing inequalities and perpetuate poverty by trapping workers in agriculture. This interaction between housing costs and agricultural employment underscores the need for policies that improve housing affordability, particularly for rural populations, to promote more inclusive economic growth.

8 Discrete Choice Model

In the reduced-form analyses, I aggregate the impacts of housing prices at potential destinations into a weighted average, treating migration as a binary decision—whether to migrate or not. However, in reality, migration is not a binary choice but a selection from multiple potential destinations, where the housing price at one destination can influence migration flows to other destinations. A discrete choice model captures this complexity by modeling migration decisions as discrete choices.

The discrete choice model can then be used to simulate the outcomes of various policy interventions, such as housing subsidies. Additionally, it allows me to assess how policy impacts vary based on targeted destination prefectures and population subgroups. By comparing simulated outcomes for different policies, the model offers insights into effective strategies for increasing migration through improved housing affordability. Additionally, it enables the evaluation of how different housing policies can reduce intergenerational persistence and barriers to structural transformation.

8.1 Setup

Since the discrete choice model generates the labor supply and housing demand for the full spatial equilibrium model in Section 9, I provide a more detailed setup in this section.

Each worker chooses to live in the prefecture that offers the most desirable combination of wages, housing prices, and moving costs. A worker residing in prefecture p supplies one unit of labor and earns a wage W_p. The worker consumes housing M at a local price of rH_p, where r is the discount factor converting purchase prices to rental prices, and a national good O with a normalized price of one. The worker maximizes Cobb-Douglas preferences for housing and the national good, subject to a budget constraint:

$$\begin{aligned} \max_{M,O} \quad & \ln\left(M^{\zeta}\right) + \ln\left(O^{1-\zeta}\right) \\ \text{s.t.} \quad & O + rH_pM \leq W_p. \end{aligned}$$

Workers' relative preference for the national good versus local housing is determined by ζ, where $0 \leq \zeta \leq 1$, and is assumed to be constant across all workers. The worker's optimized utility from consumption can be expressed as the indirect utility function, V_p, for living in prefecture p:

$$V_p = ln(W_p) - \zeta ln(rH_p) = w_p - \zeta h_p - \zeta lnr$$

where $w_p = ln(W_p)$ and $h_p = ln(H_p)$. The worker's optimized utility function also determines their housing demand, D_p:

$$D_p = \frac{\zeta W_p}{rH_p} \tag{8}$$

Additionally, worker i from origin prefecture o incurs financial and psychological moving costs, C_{ifop}, when relocating to prefecture p:

$$\begin{aligned} C_{ifop} = &\beta_f^h h_p + \beta^d lnDistance_{op} + \beta^r ruralHukou_i \times \mathbf{1}\{o \neq p\} \\ &+ \beta^m male_i \times \mathbf{1}\{o \neq p\} + \pi_f + \xi_{fp} \end{aligned}$$

The term $\beta_f^h h_p$ represents the transient residential cost incurred when a worker searches for a job upon arriving at the destination. This impact varies by parental background, f, as workers from affluent families are better equipped to cover these upfront costs. $\beta^d lnDistance_{op}$ captures transportation costs or the disutility of being far from home, which depends on the log distance between the origin and destination prefecture. A worker can also choose to stay in the origin, in which case the log distance is set to zero. β^r represents the differential cost for rural workers when migrating; they often benefit more than urban workers due to significantly improved job opportunities and amenities at the destination. β^m represents the differential migration cost between men and women. π_f is the fixed effects capturing taste differences among workers with different parental backgrounds. The residual, ξ_{fp}, captures the impacts of unobserved destination-specific characteristics, such as local amenities. Since housing prices can be correlated with local amenities and thus endogenous, I instrument housing prices using the HPR policy as in the main analysis.

Each worker has an idiosyncratic preference for each prefecture, represented by ϵ_{ifop}, drawn from a Type I Extreme Value distribution. To simplify notation and discussion of estimation, I normalize the utility function by dividing each worker's utility by the standard deviation of ϵ_{ifop}, so that ϵ_{ifop} follows a standard Type I Extreme Value distribution. For consistency and clarity, with a slight abuse of notation, I use the same notation for the parameters in the normalized utility function as in the previous unnormalized utility function expressed in wage units. β^w is a new parameter that represents the utility derived from wages. The resulting utility for a worker choosing prefecture p is:

$$U_{ifop} = \beta^w(w_p - \zeta h_p) + \beta^h_f h_p + \beta^d lnDistance_{op} + \beta^r ruralHukou_i \times \mathbf{1}\{o \neq p\}$$
$$+ \beta^m male_i \times \mathbf{1}\{o \neq p\} + \pi_f + \xi_{fp} + \epsilon_{ifop}$$

where $-\zeta lnr$ is dropped as it is a constant. I rewrite this equation as:

$$U_{ifop} = \delta_{fp} + \chi_{iop} + \epsilon_{ifop}$$

where $\delta_{fp} = \beta^w(w_p - \zeta h_p) + \beta^h_f h_p + \pi_f + \xi_{fp}$ and $\chi_{iop} = \beta^d lnDistance_{op} + \beta^r ruralHukou_i \times \mathbf{1}\{o \neq p\} + \beta^m male_i \times \mathbf{1}\{o \neq p\}$. $lnDistance_{op}$, $ruralHukou_i$, and w_p are taken as exogenous, while h_p is treated as endogenous. A worker can choose to live in the origin, in which case $o = p$.

This setup is the conditional logit model, first formulated in this utility maximization context by McFadden (1973). The probability that worker i choose to migrate to prefecture p is:

$$Pr_{ifop} = \frac{\exp\left(\delta_{fp} + \chi_{iop}\right)}{\sum_{n \in N} \exp\left(\delta_{fn} + \chi_{ion}\right)}$$

where N is the set of all prefectures.

8.2 Estimation

In practice, I utilize panel data across different prefectures and years, allowing me to exploit both cross-sectional and temporal variation for estimation. The utility obtained by a worker born in year t from origin o with parental background f when choosing to reside in prefecture p is:

$$U_{ifopt} = \beta^w w_{pt} + \beta^h_f h_{pt} + \beta^d lnDistance_{op} + \beta^r ruralHukou_i \times \mathbf{1}\{o \neq p\}$$
$$+ \beta^m male_i \times \mathbf{1}\{o \neq p\} + \pi_{ft} + \mu_p + \xi_{fpt} + \epsilon_{ifopt}$$

where some variables are allowed to vary across birth cohorts, and time-invariant prefecture fixed effects μ_p are included. I combine $-\beta^w \zeta h_{pt}$ and $\beta^h_f h_{pt}$ into $\beta^h_f h_{pt}$, as they cannot be separately identified in estimation.

The magnitudes of the coefficients on wages and housing prices reflect the elasticity of workers' demand for a small prefecture with respect to local wages and housing prices, given the functional form assumption.[17]

[17] Given the assumed distribution of workers' idiosyncratic preferences for prefectures, the elasticity of demand for workers with father's education f and birth cohort t for prefecture p with respect to local housing prices is $(1 - s_{fopt})\beta^h_f$, where s_{fopt} denotes the share of workers choosing to live in prefecture

The probability that worker i choose to migrate to prefecture p is:

$$Pr_{ifopt} = \frac{\exp\left(\delta_{fpt} + \chi_{iop}\right)}{\sum_{n \in N} \exp\left(\delta_{fnt} + \chi_{ion}\right)} \tag{9}$$

where N is the set of all destination prefectures.

I estimate the model in two steps. First, I estimate Equation (9) using maximum likelihood estimation (MLE). Secondly, I take the estimated $\hat{\delta}_{fpt}$ and apply a 2SLS estimation utilizing the implementation of HPR policy as the instrument for housing prices h_{pt} to estimate β_t^h.

In practice, there is not enough data to estimate δ_{fpt} for each birth year and each level of fathers' education. Instead, I divide the sample into early and late birth cohorts based on birth years and categorize fathers' education into high and low, i.e., both f and t are binary. This approach allows me to estimate four δ's for each prefecture. Appendix Figure B.4 shows the goodness of fit of the first step. I then use these estimate δ's to estimate the following equation using a 2SLS approach:

$$\begin{aligned} \hat{\delta}_{fpt} = {} & \beta_1 FatherEduHigh_f \times HousingPrices_{pt} + \beta_2 HousingPrices_{pt} \\ & + M'_{pt}\Theta + \mu_p + \pi_{ft} + \xi_{fpt} \end{aligned} \tag{10}$$

where $FatherEduHigh_f$ is an indicator for fathers' education being high type. M_{pt} are macroeconomic conditions, which consist of employment rate, GDP per capita, and log wage. μ_p are prefecture fixed effects, and π_{ft} are fathers' education times birth cohort fixed effects. ξ_{fpt} is the residual. Housing prices are instrumented using the HPR policy, and the interaction term $FatherEduHigh \times HousingPrices$ is instrumented by $FatherEduHigh \times HPR$.

The results of the second step are shown in Table 7. Columns (1) and (2) show the OLS estimates without and with macroeconomic controls, respectively. Columns (3) and (4) display the IV estimates, also with and without controls. The negative and significant coefficients for housing prices indicate that higher housing costs reduce a worker's utility of residing in a prefecture. The positive and significant coefficients for the interaction between fathers' education and housing prices suggest that higher paternal education partially offsets the adverse impact of housing prices, though not enough to fully counterbalance the adverse effects of high housing costs.

The coefficients on housing prices are consistent with the existing literature. Column (4) estimates show that the elasticity of workers' demand for a small prefecture with respect to local housing prices is approximately -3.606 for workers with low-education

p. For a small prefecture, where s_{fopt} is close to zero, the demand elasticity for rent is approximately β_f^h.

Table 7: Conditional Logit

	OLS		IV	
	(1)	(2)	(3)	(4)
FatherEduHigh× HousingPrices	0.380***	0.384***	0.747**	0.758**
	(0.107)	(0.110)	(0.322)	(0.326)
HousingPrices	-1.181***	-1.011***	-4.050***	-3.606**
	(0.347)	(0.376)	(1.230)	(1.436)
FatherEduHigh× birthcohort FE	√	√	√	√
Prefecture FE	√	√	√	√
Controls	-	√	-	√
K-P F-stat			12.880	7.772
LM test			19.100	9.569
Obs.	607	603	607	603
Mean(Dep. Var.)	0.178	0.180	0.178	0.180

NOTE: This table shows the estimates of equation (10). Columns (1) and (2) show the OLS estimates, both without and with macroeconomic controls, which consist of employment rate, GDP per capita, log wage, and log export. Columns (3) and (4) show the IV estimates, again with and without these controls. Standard errors are clustered at the prefecture level; ***p<0.01, **p<0.05, *p<0.1.

fathers and -2.848 for those with high-education fathers. In comparison, Diamond (2016) reports an elasticity of around -2.496 for non-college workers and -1.312 for college-educated workers, though her estimates reflect elasticity with respect to rent rather than housing purchase prices.

The results of the first stage of the 2SLS estimation are shown in Appendix Table B.13. The coefficients have the expected signs. The coefficients of the HPR policy, when housing price is the independent variable, are negative, indicating that the implementation of the HPR policy negatively affects housing prices.

The results remain robust under more complex specifications, such as incorporating workers' education, including existing migration patterns between origin and destination, adjusting thresholds for fathers' education and birth cohorts, and allowing the effects of distance and rural *Hukou* to vary by parental background.

8.3 Advantaged Migrants Respond More to Tier 1 Prices

This subsection examines how migration responses vary across parental backgrounds for different destinations. The focus is on comparing Tier-1 prefectures (Beijing, Shanghai, Shenzhen, and Guangzhou) with other areas, as Tier-1 prefectures are the primary migration destinations, attracting approximately one-third of all migrants.

I begin by analyzing the impact of a 10% decrease in housing prices faced by

Table 8: Price Sensitivity by Prefecture Type and Father's Education

	Change in Percentage Points		
Father's Education	Stay	Migrate to Tier-1	Migrate to Non-Tier-1
10% decrease in housing prices for migrants in ...			
Panel A: all prefectures			
L	-4.73	1.09	3.64
H	-4.20	1.66	2.55
Panel B: Tier-1 prefectures			
L	-1.17	1.45	-0.28
H	-1.76	2.41	-0.66
Panel C: non-Tier-1 prefectures			
L	-3.72	-0.26	3.98
H	-2.65	-0.64	3.29
Baseline Fractions			
L	85.15	3.57	11.28
H	78.1	8.97	12.93

NOTE: This table shows the percentage point changes in migration behavior among workers from different parental backgrounds in response to different housing price changes. The table displays migration responses only for workers whose origin is not Tier-1 prefectures. The "Baseline Fractions" panel shows the fractions of different types of workers before any changes in housing prices. In terms of interpreting the numbers in the table, consider the -4.73 percentage point change in Panel A. This figure reflects a reduction in the proportion of workers with low-education fathers who remain in their origin prefecture, a shift from 85.15% to 80.42%.

migrants across all prefectures. This means that migrants encounter housing prices at 90% of the actual value in any prefecture outside their origin. Panel A of Table 8 displays the percentage point changes in migration behavior resulting from this reduction. The interpretation is that, for instance, the proportion of workers with low-education fathers who remain in their origin prefecture decreases from 85.15% to 80.42%, a drop of 4.73 percentage points.

The results suggest that as housing prices decrease, migration increases, with workers from disadvantaged backgrounds being more likely to transition from staying to migrating. However, migration destinations vary by parental background. Workers with high-education fathers are more likely to migrate to Tier-1 prefectures, while those with low-education fathers migrate more to non-Tier-1 prefectures.

Next, I analyze the impact of a 10% decrease in housing prices faced by migrants in Tier-1 prefectures only. Panel B of Table 8 shows the resulting percentage point changes in migration behavior. The findings suggest that while the proportion of workers with low-education fathers migrating to Tier-1 prefectures increases by 1.45 percentage points, the increase is significantly larger for workers with high-education fathers.

The results in Table 7 in the previous subsection show that increases in housing costs reduce utility more for workers from disadvantaged backgrounds. Why, then, is migration to Tier-1 prefectures more responsive among the advantaged compared to the less advantaged? A key factor is that the high initial housing prices in Tier-1 prefectures make workers with disadvantaged backgrounds unlikely to consider migrating there. Marginal decreases in housing costs are insufficient to influence their migration decisions. In contrast, workers with high-education fathers are more likely to be at the margin of deciding to migrate to Tier-1 prefectures. This aligns with the model in Section 4, which explains how the varying impacts of housing prices across parental backgrounds depend on both the differences in migration costs and the relative number of children at the margin in each group.

Additional tests suggest that the greater distances to Tier-1 prefectures also contribute to fewer children with low-education fathers being at the margin compared to those with high-education fathers. However, simply reducing the distance gap between the two groups is insufficient to prompt a larger response to housing price changes among children with low-education fathers compared to those with high-education fathers.

Finally, I turn to the impact of a 10% decrease in housing prices for migrants in non-Tier-1 prefectures. Panel C of Table 8 presents the results. Unlike the housing price changes in Tier-1 prefectures, changes in non-Tier-1 prefectures have a greater impact on the migration behavior of workers with low-education fathers compared to those with high-education fathers. For both groups, the impacts are significantly larger than the previous policies due to the broader coverage of destination prefectures.

Overall, the three analyses indicate that policy design should consider the nature of the different destination prefectures. In Tier-1 prefectures, a targeted approach appears more effective in encouraging migration among workers from disadvantaged families, while in non-Tier-1 prefectures, targeting may not be necessary. The counterfactual analyses in the next section further support these conclusions.

9 Spatial Equilibrium Model

The above analyses focus on the household side without addressing the effects of migration on destination prefectures. However, migration undoubtedly has general equilibrium effects. For instance, a decline in housing prices in a prefecture attracts more migrants, which in turn drives up housing prices due to increased demand, limiting further migration. This section incorporates these general equilibrium effects and simulates the counterfactual outcomes for the three policies discussed in the previous section. Moreover, I provide back-of-the-envelope calculations to assess the impacts on intergenerational persistence, agricultural employment, and the associated fiscal expenditure.

The spatial equilibrium model follows a standard framework with one tweak: housing price impacts vary by parental background. It extends the discrete choice model from the previous section by incorporating a housing market that adjusts housing prices in response to changes in population size.

9.1 Setup

9.1.1 Labor Demand

I assume that firms in each prefecture produce a homogeneous tradable good using identical constant returns to scale technology. Thus, firm-level labor demand directly reflects prefecture-level aggregate labor demand. Each prefecture has a representative profit-maximizing firm, with output prices normalized to one. In each prefecture p for birth cohort t, the representative firm takes productivity A_{pt} as given and produces output using the production function:

$$Y_{pt} = A_{pt} L_{pt}$$

where L stands for labor in the prefecture. Since there are a large number of firms and no barriers to entry, the labor market is perfectly competitive, and firms hire such that wages equal the marginal product of labor. Namely $w_{pt} = lnA_{pt}$. Wages are exogenous and remain unaffected by changes in the prefecture's population size.

9.1.2 Housing Supply

Following Diamond (2016), housing production depends on construction materials and land, with developers acting as price-takers and selling homogenous houses at marginal cost:

$$h_{pt} = MC(\kappa_{pt}, \nu_{pt})$$

where $MC(\kappa_{pt}, \nu_{pt})$ is the marginal cost function based on local construction costs κ_{pt} and land costs ν_{pt}. Land cost ν_{pt} is a function of aggregate housing demand. The log housing supply equation is parameterized as follows:

$$h_{pt} = \ln(\kappa_{pt}) + \gamma \ln(D_{pt}) \tag{11}$$

Here, γ represents the elasticity of housing prices with respect to demand, which will be calibrated from the literature. D_{pt} is the housing demand derived from workers maximizing their Cobb-Douglas preferences for housing and the national good, subject to a budget constraint. As outlined in Section 8.1, equation (8), housing demand is given by $D_{pt} = \frac{\zeta W_{pt}}{r H_{pt}}$. $\ln(\kappa_{pt})$ is unobserved and included in the residuals.

9.1.3 Equilibrium

Equilibrium in this model is defined by a menu of wages and housing prices $\{w_{pt}, h_{pt}\}$ with populations $\{L_{pt}\}$, such that:

- The labor demand equals labor supply:

The labor demand function is given by:

$$w_{pt} = lnA_{pt}$$

Labor supply is the total expected population of prefecture p for birth cohort t, calculated as the sum of the probabilities that each worker chooses to reside in this prefecture.

$$L_{pt} = \sum_{i \in L_t} \frac{\exp\left(\delta_{fpt} + \chi_{iop}\right)}{\sum_{n \in N} \exp\left(\delta_{fnt} + \chi_{ion}\right)} \tag{12}$$

where L_t represents the set of workers in birth cohort t across the nation. $\delta_{fpt} = \beta^w w_{pt} + \beta^h_f h_{pt} + \pi_{ft} + \mu_p + \xi_{fpt}$ and $\chi_{iop} = \beta^d lnDistance_{op} + \beta^r ruralHukou_i \times \mathbf{1}\{o \neq p\} + \beta^m male_i \times \mathbf{1}\{o \neq p\}$.

- Housing demand equals housing supply:

By combining the housing demand function in equation (8) with the housing supply function in equation (11), I derive the following:

$$h_{pt} = \Gamma lnL_{pt} + \Gamma w_{pt} + \varepsilon_{pt} \tag{13}$$

where $\Gamma = \frac{\gamma}{1+\gamma}$ and $\varepsilon_{pt} = \Gamma(ln\zeta - lnr) + (1-\Gamma)ln\kappa_{pt}$

For this simple setup, I only need the estimates from the discrete choice model. The key parameter for the housing market, Γ, is calibrated based on the existing literature. The results are similar across different values of Γ in the literature.

9.2 Counterfactual Analysis

Using the full model, I estimate the impacts of three counterfactual policies on migration and provide back-of-the-envelope calculations for their effects on intergenerational persistence and agricultural employment. Counterfactuals are obtained through iteration, with the detailed procedure outlined in Appendix Section E.

Table 9: Counterfactual Analysis of Migration Responses to Rent Subsidy Policies

	Change in Percentage Points		
FatherEdu	Stay	Migrate to Tier-1	Migrate to Non-Tier-1
Panel A: 10% Rent Subsidy in Tier-1 Prefectures			
L	-0.79	1.01	-0.22
H	-1.20	1.70	-0.49
Panel B: 10% Rent Subsidy in Tier-1 Prefectures for Migrants with Low-Education Fathers			
L	-0.92	1.18	-0.26
H	0.23	-0.29	0.06
Panel C: 10% Rent Subsidy in Non-Tier-1 Prefectures			
L	-3.25	-0.21	3.46
H	-2.35	-0.49	2.84
Baseline Fractions			
L	85.15	3.57	11.28
H	78.1	8.97	12.93

NOTE: This table shows the percentage point changes in migration behavior among workers from different parental backgrounds in response to each policy. The table displays migration responses only for workers whose origin is not Tier-1 prefectures. The "Baseline Fractions" panel shows the fractions of different types of workers before any changes in housing prices. In terms of interpreting the numbers in the table, consider the -0.79 percentage point change in Panel A: it reflects a reduction in the proportion of workers with low-education fathers remaining in their origin prefecture, from 85.15% to 84.36%.

I first analyze the impact of a housing price regulation policy that offers migrants a 10% rent subsidy in Tier-1 prefectures. In other words, migrants face housing prices that are 90% of the actual prices in Tier-1 prefectures. Panel A of Table 9 shows the percentage point changes in migration behavior resulting from the policy. The results imply that while the fraction of workers with low-education fathers who migrate to Tier-1 prefectures increases by 1.01 percentage points, the increase is again much larger for those with high-education fathers.

The results above indicate that a more targeted approach may be more effective in encouraging migration among children from disadvantaged families. I thus evaluate the impact of a targeted housing subsidy policy that offers a 10% discount in Tier-1 prefectures specifically for migrants whose fathers have low education levels. Under this policy, migrants with low-education fathers face housing prices at 90% of the actual value, while those with highly educated fathers face the full prices. Table 9 Panel B shows the results. This targeted approach significantly increases migration among workers with low-education fathers. Notably, a small number of workers with high-education fathers are displaced as the increased influx of disadvantaged migrants causes a slight rise in Tier-1 housing prices.

An alternative policy is to provide rent subsidies in non-Tier-1 prefectures, which might require lower fiscal expenditure due to their relatively lower rents compared to Tier-1 prefectures. A non-targeted policy also reduces the risk of workers' misreporting parental backgrounds, which is difficult to verify. Under this policy, migrants would face housing prices at 90% of the actual prices in non-Tier-1 prefectures. Panel C of Table 8 presents the results. Unlike subsidies in Tier-1 prefectures, subsidies in non-Tier-1 prefectures have a greater impact on the migration behavior of workers with low-education fathers compared to those with high-education fathers. For both groups, the impacts are significantly larger than the previous policies due to the broader coverage of destination prefectures.

Overall, the three counterfactual analyses indicate that policy design should consider the nature of the different destination prefectures. In Tier-1 prefectures, a targeted approach is more effective in increasing migration among workers from disadvantaged families, whereas, in non-Tier-1 prefectures, targeting is not necessary.

I also assess the impacts on intergenerational persistence, measured by the income gap between workers from different parental backgrounds. On average, workers with high-education fathers earn 22% more than those with low-education fathers. A 10% rent subsidy for all migrants in Tier-1 prefectures increases this gap by 0.59 percentage points, or approximately 3% of the initial difference, as more high-education workers migrate and earn higher incomes than their low-education counterparts. In contrast, a targeted 10% rent subsidy for migrants with low-education fathers reduces the gap by 13%, significantly improving intergenerational mobility. A 10% rent subsidy in non-Tier-1 prefectures narrows the gap by 4%, a smaller effect due to lower income levels in these areas and the simultaneously increased migration among workers with high-education fathers.

For the calculations on agricultural employment, I restrict the sample to workers from rural areas. Those who remain in their origin prefecture are assumed to work in agriculture with a probability equal to the share of rural workers employed in the agricultural sector within that prefecture. Migrants are assumed to work in the non-agricultural sector. Back-of-the-envelope calculations show that a 10% rent subsidy for all migrants in Tier-1 prefectures increases the agricultural employment gap between workers with low- and high-education fathers by 3%. In contrast, a targeted 10% rent subsidy for migrants with low-education fathers reduces the gap by 6%. A 10% rent subsidy in non-Tier-1 prefectures narrows the gap by 5%. The results imply that to promote structural transformation and encourage rural-to-urban migration, the second and third policies are similarly effective.

10 Conclusion

This paper examines the relation between housing affordability, internal migration, and intergenerational mobility in China, highlighting the multifaceted impact of rising housing costs on socioeconomic disparities. Utilizing the HPR policy as a natural experiment and an instrumental variable approach, this paper documents that elevated housing costs significantly deter internal migration, with disproportionately adverse effects on children from less privileged backgrounds. This dynamic exacerbates income disparities and diminishes intergenerational mobility, reinforcing the cycle of economic disadvantage.

The findings in this paper suggest that in China, a country characterized by geographical inequality (Xie and Zhou, 2014) and low intergenerational mobility, implementing housing price regulations has the potential to alleviate both concerns by encouraging greater internal migration. This implication somewhat relates to the literature explaining the mechanism behind the Great Gatsby Curve, which refers to the positive correlation between inequality and intergenerational persistence observed in many countries. While the literature focuses on education attainment as a main mechanism, this paper points out that even with the same education, access to opportunities is different with different parental backgrounds.

This paper's conceptual framework is relevant in many developing countries where migration plays crucial roles in social mobility. Future research could explore comparative studies across countries with diverse housing markets and migration policies to provide a broader perspective on the global impact of housing affordability on intergenerational mobility.

In conclusion, this research emphasizes the need for targeted policies to address housing affordability and enhance economic equality and social mobility. As housing prices rise globally, it is crucial to understand their impact on migration patterns. Moreover, the findings suggest that high-skill children from disadvantaged families can be trapped in rural areas while low-skill children from affluent families easily migrate. These findings are relevant for the broader discussions on spatial labor misallocation and productivity (Young, 2013). Reducing housing costs could help narrow the gap in migration behaviors, leading to substantial gains in both equity and efficiency.

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A Appendix: Continuous Model

This section shows a continuous version of the model where, instead of High and Low type, both children's income and fathers' socioeconomic status are continuous. The model is based on Borjas (1987) and Chiquiar and Hanson (2005). The model suggests that housing price changes may increase or decrease migration and then intergenerational mobility, depending on parameters and specific distributions of disutility with respect to migration.

I assume that if a child stays at the origin, they get $Y_{stay} = \mu_0 + \delta_0 F$; if the children migrate, they get $Y_{migrate} = \mu_1 + \delta_1 F$. Migration requires a cost of $M(h, F)$, which depends on the housing price gap h and the father's socioeconomic status F. I assume that $\frac{\partial M(h,F)}{\partial h} > 0$, meaning that an increase in housing price gaps increases migration cost. People also have mental costs for migration, which I call "disutility" and denote as τ. τ is independent of F and the realized Y. I denote the CDF and PDF function of τ as $G_\tau(\tau)$ and $g_\tau(\tau)$

This model makes the following assumptions. First, instead of analyzing the heterogeneity with respect to the potential migrants' education as in Borjas (1987), I assume here that each individual has the same level of education, and the father's socioeconomic status, F, affects the children's income, Y. Second, the disutility function is independent of F and the realized Y.

Combining the above benefit and cost, a child will migrate if:

$$Y_{migrate} - M(h, F) - \tau > Y_{stay} \tag{14}$$

Rearrange the equation and substitute $Y_{migrate}$ and Y_{stay}, the above equation is equivalent to:

$$(\mu_1 - \mu_0) + (\delta_1 - \delta_0)F - M(h, F) > \tau \tag{15}$$

Denote the left-hand side as $B(h, F)$, which is the net benefit of migrating. For a child faced with their father's socioeconomic status F and housing price gap h, the probability that they migrate is $Pr(migrate|h, F) = Pr(B(h, F) > \tau) = G_\tau(B(h, F))$.

In my main regression analysis, I regress the migration indicator on the interaction of paternal socioeconomic status and the housing price gap. The coefficient of interest, the cross derivative of migration probability with respect to the housing price gap and the father's socioeconomic status, can be derived from the model.

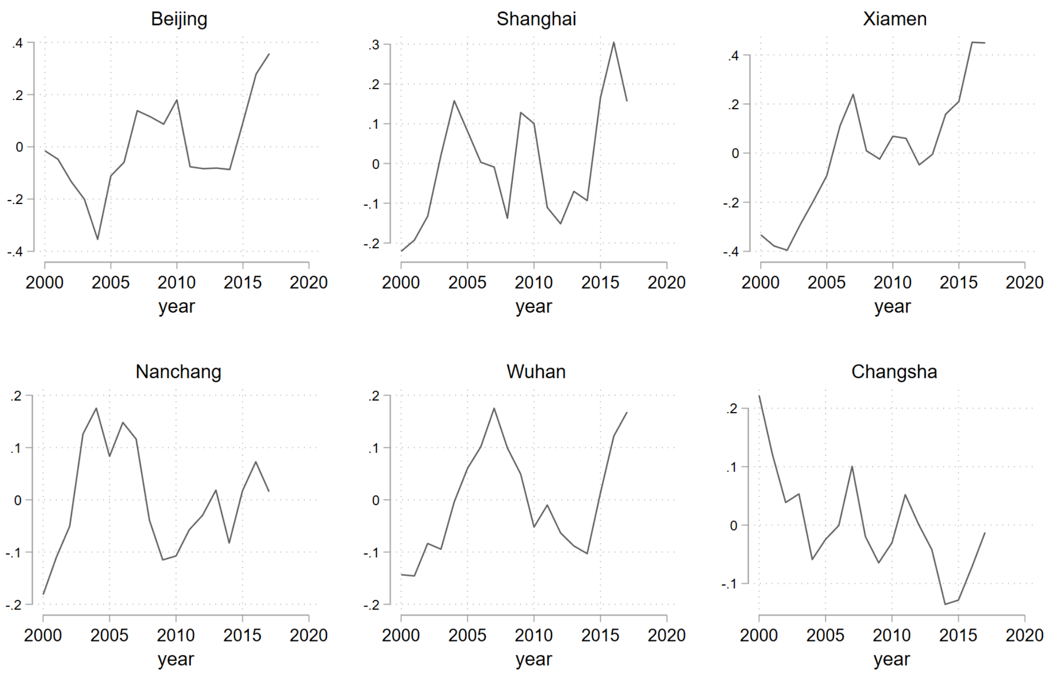
$$\frac{\partial^2 Pr(migrate|h,F)}{\partial h \partial F} = \underbrace{[-g_\tau(B)M''_{Fh}]}_{\text{heterogeneous cost}} + \underbrace{[-g'_\tau(B)B'_F M'_h]}_{\text{position at disutlity distribution}}$$

Similarly, I derive the cross derivative of the expected income with respect to h and F:

$$\frac{\partial^2 E[Y|h,F]}{\partial h \partial F} = \underbrace{[-(B+M)g_\tau(B)M''_{Fh}]}_{\text{heterogeneous cost}} + \underbrace{[-(B+M)g'_\tau(B)B'_F M'_h]}_{\text{position at disutility distribution}} + \underbrace{[-(\delta_1-\delta_0)g_\tau(B)M'_h]}_{\text{heterogeneous benefit}}$$

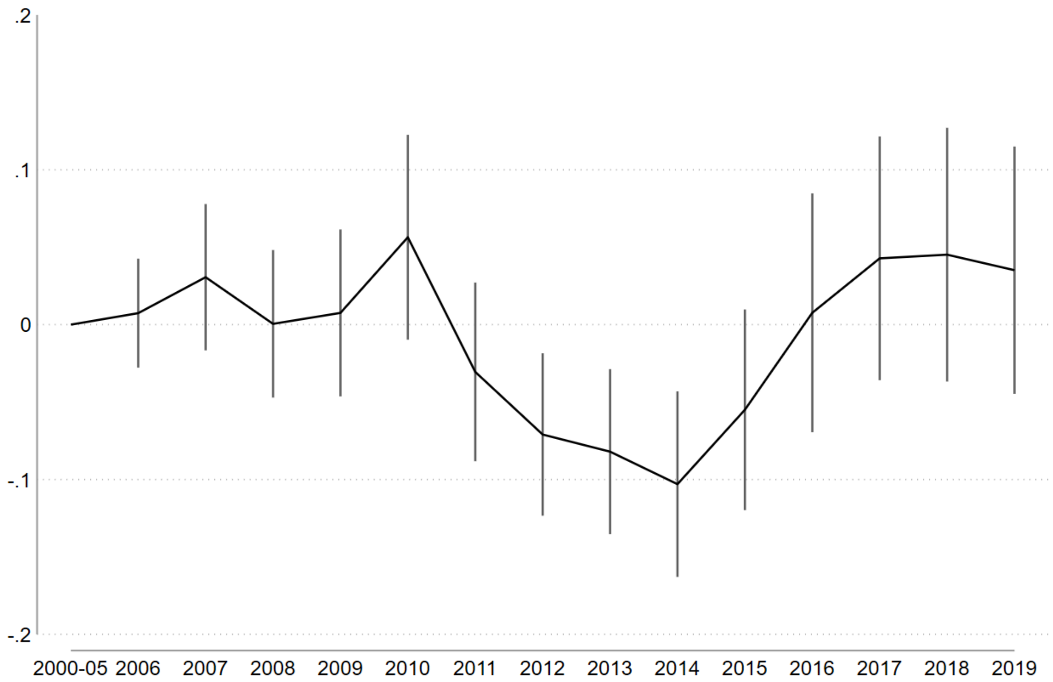
B Appendix: Figures and Tables

Figure B.1: Housing price residuals in six major prefectures in China



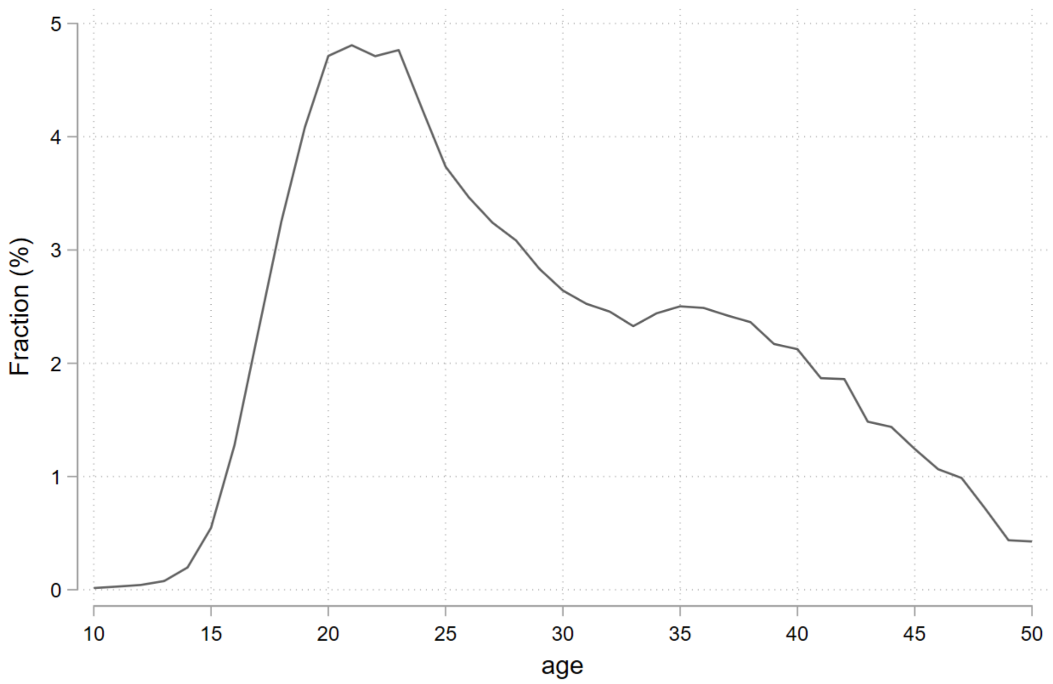
NOTE: The figure shows the residualized housing prices obtained from regressing housing prices (measured by log yuan per square meter in 2000RMB) on prefecture fixed effects and year fixed effects. The figure underscores the considerable temporal and regional variation across prefectures.

Figure B.2: HPR Event Study Plot



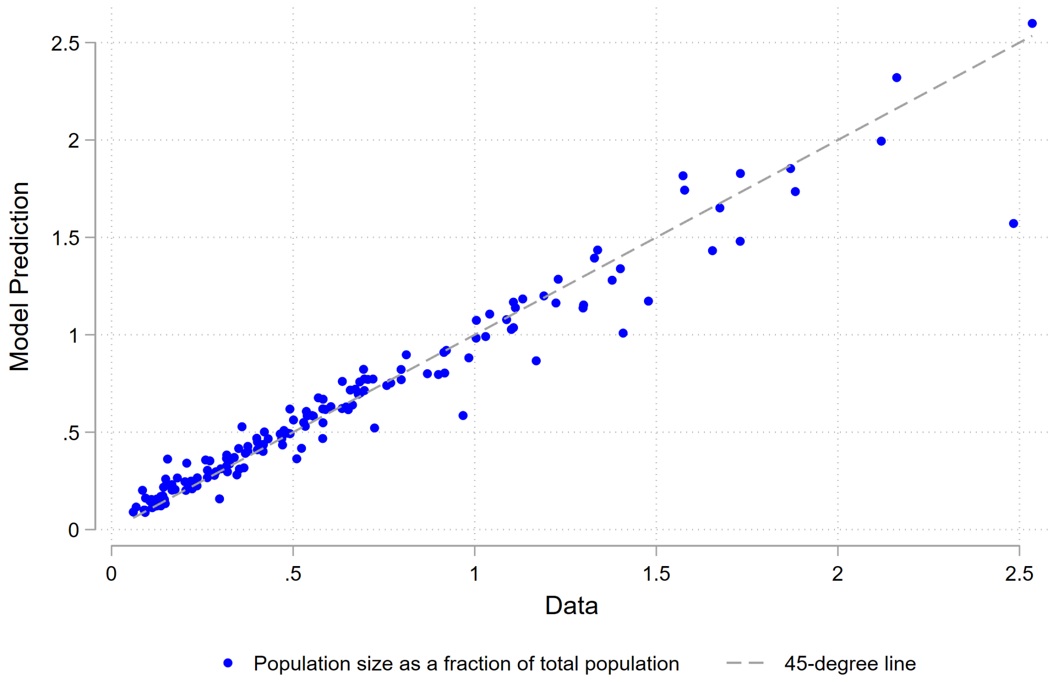
NOTE: The figure shows the event study plot for the HPR policy. Using the prefecture-year-level panel data, housing prices are regressed on prefecture fixed effects, year fixed effects, and interaction terms between year dummies and an indicator for ever adopted the policy. The figure shows the estimates and confidence intervals for the coefficients of the interaction terms, which reflect the changes in differences in housing prices between the ever-treated and never-treated prefectures over time.

Figure B.3: Age-specific Migration Probability



NOTE: The figure shows the age-specific migration probability rate, which is the proportion of people who migrated at a specific age out of the total number of migrants.

Figure B.4: Goodness of Fit: Predicted vs. Actual Population Size



NOTE: The figure shows the observed and predicted population sizes for each prefecture as a fraction of the total population. Each dot represents a specific prefecture.

Table B.1: Numerical Example of Housing Price Gap Construction

		Housing Price (w_{od})		
Age (a_k)	**Year**	**Destination 1 (25%)**	**Destination 2 (75%)**	**Origin**
19 (20%)	t+19	5	3	1
20 (80%)	t+20	6	4	2
Weighted by a_k		5*20%+6*80% = 5.8	3*20%+4*80% = 3.8	1*20%+2*80% = 1.8
Weighted by w_{od}		5.8*25%	3.8*75%	
Final HPgap		5.8*25% + 3.8*75% - 1.8 = 2.5		

NOTE: This table provides a numerical example of how the housing price gap measure is constructed for workers originating from prefecture o and born in year t. a_k represents the age-specific migration probability for age k, which is used as the weight for housing prices in year $(t+k)$, where t is the birth year. Here, k is either 19 or 20 for simplicity. w_{od} is the migration pattern weight, and d denotes either Destination 1 or Destination 2. The main sources of variation in housing price gaps across workers are the differing migration pattern weights based on their origin and the varying price shocks experienced by workers born in different years.

Table B.2: The List of 46 Prefectures that Adopted the Housing Purchase Restriction Policy with Dates of Announcing and Abolishing the Policy

Prefecture	Start Year	Start Month	End Year	End Month
Beijing	2010	4		
Tianjin	2010	10	2014	10
Shijiazhuang	2011	2	2014	9
Taiyuan	2011	1	2014	8
Huhehaote	2011	4	2014	6
Shenyang	2011	3	2014	9
Dalian	2011	3	2014	9
Changchun	2011	5	2015	6
Haerbin	2011	2	2014	8
Shanghai	2010	10		
Nanjing	2010	10	2014	9
Wuxi	2011	2	2014	8
Xuzhou	2011	5	2014	8
Suzhou	2011	3	2014	9
Hangzhou	2010	10	2014	8
Ningbo	2010	10	2014	7
Wenzhou	2011	3	2013	8
Shaoxing	2011	8	2014	8
Jinhua	2011	3	2014	8
Quzhou	2011	9	2014	7
Zhoushan	2011	8	2013	1
Taizhou	2011	8	2014	8
HeFei	2011	1	2014	8
Fuzhou	2010	10	2014	8
Xiamen	2010	10	2014	8
Nanchang	2011	2	2014	7
Jinan	2011	1	2014	7
Qinghai	2011	1	2014	9
Zhengzhou	2011	1	2014	8
Wuhan	2011	1	2014	7
Changsha	2011	3	2014	8
Guangzhou	2010	10		
Shenzhen	2010	9		
Zhuhai	2011	11	2016	3
Foshan	2011	3	2014	8
Nanning	2011	3	2014	10
Haikou	2010	10	2014	7
Sanya	2010	10		
Chengdu	2011	2	2015	1
Guiyang	2011	2	2014	9
Kunming	2011	1	2014	8
Xian	2011	3	2014	9
Lanzhou	2011	3	2014	7
Xining	2011	8	2014	9
Yinchuan	2011	2	2014	8
Wulumuqi	2011	3	2014	8

NOTE: This table lists the dates of announcing and abolishing the Housing Purchase Restriction Policy according to Chen et al. (2017).

Table B.3: Descriptive Statistics

	Mean	SD
Migration	0.20	0.40
lnIncome	9.80	1.67
FatherEduy	5.74	4.51
HPgap	0.51	0.51
Male	0.46	0.50
Eduy	10.05	3.75
Rural Hukou	0.67	0.47
Age	43.19	8.95

NOTE: This table presents descriptive statistics for the main sample, which includes 14,976 observations. While the table displays mean values, fathers' years of education and the housing price gap have been demeaned in the analyses.

Table B.4: IV Results: First Stage

	(1) HPgap	(2) FatherEduy× HPgap	(3) HPgap	(4) FatherEduy× HPgap	(5) HPgap	(6) FatherEduy× HPgap
HPR	-0.1653***	4.4652***	-0.1610***	3.0489***	-0.1626***	3.1662***
	(0.0139)	(0.3927)	(0.0139)	(0.4377)	(0.0139)	(0.4335)
FatherEduy× HPR	0.0015**	2.2914***	0.0004	2.6472***	-0.0004	2.7095***
	(0.0006)	(0.0600)	(0.0006)	(0.0568)	(0.0006)	(0.0567)
FatherEduy× birthyearFE	-	-	√	√	√	√
Eduy× birthyearFE	-	-	-	-	√	√
Obs.	14,976	14,976	14,976	14,976	14,976	14,976
Adj. R-sq	0.9951	0.4555	0.9952	0.4937	0.9952	0.4947

NOTE: The figure shows the first-stage results. When included, Eduy×HPgap is also instrumented using Eduy×HPR. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

Table B.5: Robustness: Additional Controls

	(1) Migration	(2) Migration	(3) Migration	(4) Migration	(5) lnIncome	(6) lnIncome	(7) lnIncome	(8) lnIncome
FatherEduy× HPgap	0.010***	0.009***	0.009***	0.006**	0.033***	0.036***	0.022*	0.029**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.011)	(0.012)	(0.012)	(0.012)
HPgap			-0.716**	-0.656**			-0.562	-0.718
			(0.291)	(0.286)			(1.552)	(1.552)
Eduy× HPgap		0.004		0.009***		-0.012		-0.022
		(0.004)		(0.003)		(0.017)		(0.014)
OriginFE× BirthyearFE	√	√	-	-	√	√	-	-
Interaction terms	-	-	√	√	-	-	√	√
Obs.	14,976	14,976	14,976	14,976	12,068	12,068	12,068	12,068
Mean(Dep. Var.)	0.202	0.202	0.202	0.202	9.799	9.799	9.799	9.799

NOTE: This table shows the results of adding more controls. Fathers' years of education interacted with birth year fixed effects are controlled in all columns. Control variables include gender, parental *Hukou* status, log wage, log employment, and log export at the origin prefecture, the weighted average of the log wage, log employment, and log export at the potential destination prefectures, fixed effects for origin prefecture, birth year, and education.

Table B.6: Robustness: Control for the Price of Non-Housing Goods

	(1) Migration	(2) Migration	(3) lnIncome	(4) lnIncome
FatherEduy× HPgap	0.010***	0.007***	0.020*	0.026**
	(0.002)	(0.002)	(0.010)	(0.011)
HPgap	-0.769**	-0.695**	-2.300	-2.615*
	(0.317)	(0.311)	(1.514)	(1.529)
FatherEduy× COL	0.000**	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
COL	0.012*	0.012*	0.029	0.029
	(0.006)	(0.006)	(0.026)	(0.026)
Eduy× HPgap		0.008***		-0.017
		(0.003)		(0.013)
K-P F-stat	34.964	23.696	50.448	34.330
LM test	61.221	62.083	93.813	95.933
Obs.	14,976	14,976	12,068	12,068
Mean(Dep. Var.)	0.202	0.202	9.798	9.798

NOTE: This table shows the results of controlling for non-housing cost of living. Fathers' years of education interacted with birth year fixed effects are controlled in all columns. Control variables include gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and the individual's own education level. For Columns (1)-(2), log wage, log employment, and log export at the origin prefecture, the weighted average of the log wage, log employment, and log export at the potential destination prefectures are controlled in addition.

Table B.7: Robustness: Sample Construction

	(1) Migration	(2) Migration	(3) Migration	(4) Migration	(5) lnIncome	(6) lnIncome	(7) lnIncome	(8) lnIncome
FatherEduy× HPgap	0.009***	0.008***	0.010***	0.010***	0.027**	0.027**	0.031**	0.030**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.013)	(0.013)	(0.015)	(0.015)
HPgap	-0.699*	-0.868**	-0.660*	-0.765*	-3.009*	-3.335**	-2.664*	-3.566*
	(0.371)	(0.412)	(0.363)	(0.436)	(1.600)	(1.654)	(1.587)	(1.931)
Exclude	-	adjacent to tier-1	high GDP per capita	popular destinations	-	adjacent to tier-1	high GDP per capita	popular destinations
Obs.	14,976	14,256	14,525	14,014	12,068	11,500	11,718	11,277
Mean(Dep. Var.)	0.202	0.203	0.206	0.212	9.798	9.788	9.775	9.751

NOTE: This table shows the robustness results for different samples. Fathers' years of education interacted with birth year fixed effects and individual's education interacted with the housing price gap are controlled for in all columns. Control variables include gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and the individual's own education level. For Columns (1)-(4), log wage, log employment, and log export at the origin prefecture, the weighted average of the log wage, log employment, and log export at the potential destination prefectures are controlled in addition. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

Table B.8: Robustness: Alternative Housing Price Dataset

	(1) Migration	(2) Migration	(3) lnIncome	(4) lnIncome
FatherEduy× HPgap	0.011***	0.008***	0.025**	0.036***
	(0.002)	(0.002)	(0.010)	(0.011)
HPgap	-1.738***	-1.559***	-4.146*	-5.226**
	(0.564)	(0.542)	(2.203)	(2.291)
Eduy× HPgap		0.009***		-0.034**
		(0.003)		(0.015)
K-P F-stat	19.678	13.592	27.980	19.316
Obs.	14,950	14,950	12,049	12,049
Mean(Dep. Var.)	0.201	0.201	9.799	9.799

NOTE: This table shows the results leveraging the Anjuke data using the HPR policy treatment as the instrumental variable. Fathers' years of education interacted with birth year fixed effects are controlled for in all columns. Control variables include gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and the individual's own education level. For Columns (1) and (2), log wage, log employment, and log export at the origin prefecture, the weighted average of the log wage, log employment, and log export at the potential destination prefectures are controlled in addition. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

Table B.9: Robustness: Average Income Across Waves

	(1)	(2)	(3)	(4)
	lnIncome	lnIncome	lnIncome multi-year	lnIncome multi-year
FatherEduy× HPgap	0.021**	0.027***	0.022***	0.027***
	(0.009)	(0.010)	(0.008)	(0.009)
HPgap	-2.720**	-3.009**	-3.082**	-3.349***
	(1.327)	(1.351)	(1.240)	(1.256)
Eduy× HPgap		-0.016		-0.014
		(0.013)		(0.012)
K-P F-stat	62.223	41.908	60.816	40.854
LM test	107.637	110.246	105.610	107.910
Obs.	12,068	12,068	12,843	12,843
Mean(Dep. Var.)	9.798	9.798	9.317	9.317

NOTE: This table presents results using the log of average income across waves, as opposed to using children's income solely from 2017. The average income calculation only includes data from waves where the worker's residential prefecture remained the same as that of 2017. Notably, about 66% of the observations incorporate income data from multiple waves. For these observations, the income is averaged across the relevant waves and adjusted for the Consumer Price Index (CPI). The analysis controls for fixed effects associated with the observed waves, such as 'observed in both 2015 and 2017'. Additionally, all columns include controls for fathers' education interacted with birth year fixed effects. Columns (1) and (2) replicate results from Table 2 Columns (1) and (2). Differences in observations between Columns (3) and (4) versus (1) and (2) arise when income data from 2015 or 2019 are available for workers missing income data in 2017. Standard errors are clustered at the prefecture-birth year level, with significance levels indicated as follows: ***p<0.01, **p<0.05, *p<0.1.

Table B.10: Robustness: Residualized Fathers' Education

	(1) Migration	(2) Migration	(3) lnIncome	(4) lnIncome
FatherEduy_r× HPgap	0.009***	0.008***	0.024**	0.027**
	(0.002)	(0.002)	(0.012)	(0.012)
HPgap	-0.818***	-0.818***	-2.493*	-2.474*
	(0.315)	(0.315)	(1.392)	(1.392)
Eduy× HPgap		0.002		-0.014
		(0.004)		(0.017)
K-P F-stat	35.520	23.678	53.252	35.505
LM test	61.091	61.091	91.183	91.211
Obs.	13,046	13,046	10,490	10,490
Mean(Dep. Var.)	0.147	0.147	9.743	9.743

NOTE: This table shows the results using residualized fathers' years of education to measure parental background. The number of observations differs from the main analyses because some prefecture-by-birth-year cells contain singletons. These singletons are dropped because the residualized father's education cannot be obtained for them. Residualized fathers' years of education interacted with birth year fixed effects are controlled for in all columns. In Columns (1) and (3), the endogenous variables are $HPgap$ and $FatherEduy\_r \times HPgap$; the instrumental variables are HPR and $FatherEduy\_r \times HPR$. In Columns (2) and (4), the endogenous variables are $HPgap$, $FatherEduy\_r \times HPgap$, and $Eduy \times HPgap$; the instrumental variables are HPR, $FatherEduy\_r \times HPR$, and $Eduy \times HPR$. Control variables include gender, parental *Hukou* status, log wage and log employment at the origin prefecture, weighted averages of the log wage and log employment at the potential destination prefectures, fixed effects for origin prefecture, birth year, and education. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

Table B.11: Intergenerational Income Elasticity (IGE)

	(1) lnIncome	(2) lnIncome
lnFatherIncome	0.381^{***}	0.384^{***}
	(0.059)	(0.059)
lnFatherIncome× HPgap	0.311^{*}	0.392^{**}
	(0.167)	(0.183)
HPgap	-3.107^{**}	-3.373^{***}
	(1.267)	(1.294)
Eduy× HPgap		-0.014
		(0.013)
K-P F-stat	67.002	44.822
LM test	113.223	115.546
Obs.	12,051	12,051
Mean(Dep. Var.)	9.798	9.798

NOTE: This table shows the results using imputed fathers' income in place of fathers' education. In Column (1), the endogenous variables are $HPgap$ and $FatherIncome \times HPgap$; the instrumental variables are HPR and $FatherIncome \times HPR$. In Columns (2), the endogenous variables are $HPgap$, $FatherIncome \times HPgap$, and $Eduy \times HPgap$; the instrumental variables are HPR, $FatherIncome \times HPR$, and $Eduy \times HPR$. Control variables include gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and education. The K-P F-stat row shows the F-stats of the first stages. The LM test row shows the statistics for the underidentification test. A rejection of the null indicates that the matrix of first-stage coefficients has full column rank, i.e., the model is identified. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

Table B.12: Robustness: Impute Household Assets

	(1) Migration	(2) Migration	(3) Migration	(4) lnIncome	(5) lnIncome	(6) lnIncome
lnHHAssets	0.061***			0.277***		
	(0.010)			(0.043)		
lnHHAssets× HPgap	0.108***	0.128***	0.092***	0.195*	0.246**	0.301**
	(0.026)	(0.025)	(0.027)	(0.118)	(0.107)	(0.117)
HPgap	-0.900***	-0.904***	-0.796***	-3.282***	-2.827**	-3.105**
	(0.294)	(0.304)	(0.296)	(1.257)	(1.282)	(1.318)
Eduy× HPgap	-	-	√	-	-	√
lnHHAssets× birthyearFE	-	√	√	-	√	√
K-P F-stat	39.963	37.999	25.726	66.907	64.315	43.163
LM test	69.862	67.735	68.649	112.673	108.986	111.979
Obs.	14,955	14,955	14,955	12,051	12,051	12,051
Mean(Dep. Var.)	0.202	0.202	0.202	9.798	9.798	9.798

NOTE: This table shows the results using imputed household assets in place of fathers' education. Imputed household assets interacted with birth year fixed effects are controlled in all columns. In Columns (1) and (3), the endogenous variables are $HPgap$ and $lnHHAssets \times HPgap$; the instrumental variables are HPR and $lnHHAssets \times HPR$. In Columns (2) and (4), the endogenous variables are $HPgap$, $lnHHAssets \times HPgap$, and $Eduy \times HPgap$; the instrumental variables are HPR, $lnHHAssets \times HPR$, and $Eduy \times HPR$. Control variables include gender, parental *Hukou* status, fixed effects for origin prefecture, birth year, and the individual's own education level. For Columns (1) and (2), log wage, log employment, and log export at the origin prefecture, the weighted average of the log wage, log employment, and log export at the potential destination prefectures are controlled in addition. The K-P F-stat row shows the F-stats of the first stages. The LM test row shows the statistics for the underidentification test. A rejection of the null indicates that the matrix of first-stage coefficients has full column rank, i.e., the model is identified. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

Table B.13: Conditional Logit: First Stage

	(1) HousingPrices	(2) FatherEduHigh× HP	(3) HousingPrices	(4) FatherEduHigh× HP
HPR	-0.140***	-0.419***	-0.121***	-0.407***
	(0.027)	(0.038)	(0.030)	(0.039)
FatherEduHigh× HPR	0.002	0.697***	0.002	0.692***
	(0.003)	(0.069)	(0.003)	(0.069)
FatherEduHigh× birthcohort FE	√	√	√	√
Prefecture FE	√	√	√	√
Controls	-	-	√	√
Obs.	607	607	603	603

NOTE: Standard errors are clustered at the prefecture level. HP is the abbreviation for housing prices. Columns (1) and (2) show the estimates without macroeconomic controls. Columns (3) and (4) show the results with macroeconomic controls, including employment rate, GDP per capita, log wage, and log export.

C Appendix: Discussion on Whether to Control for Macroeconomic Conditions

When using migration as the outcome variable, macroeconomic conditions should be controlled as they are potential confounders. For example, housing price changes can influence wages through their impact on the construction industry. Since wages affect migration decisions, they are an omitted variable and must be included as a control. The same argument applies to other macroeconomic factors.[18] In practice, including the macroeconomic conditions results in minimal changes, so I do not consider them a major concern.

When using income as the outcome variable, concerns arise regarding the issue of bad control in addition to omitted variable bias. The argument for omitted variable bias is similar to the discussion above. Without controlling for macroeconomic conditions, the impact of HPR on migration reflects the combined effects of changes in housing prices and macroeconomic conditions. Since higher housing prices reduce migration and better macroeconomic conditions increase it, the estimated impact on migration—and consequently on income—is attenuated.

On the other hand, including macroeconomic controls can lead to bad control issues which also attenuate the estimates. Housing prices affect income by influencing a worker's choice of residential location, and current macroeconomic conditions in that location impact income. Since these conditions are the pathway through which housing prices affect income, controlling them introduces the bad control problem. Controlling for historical macroeconomic conditions can cause similar issues, as historical and current conditions are highly correlated, potentially absorbing some of the impact of housing prices on income.

Table C.1 presents the results for both outcomes, without and with macroeconomic controls. The coefficients of interest remain similar across specifications, indicating that these controls do not significantly affect the results. In the main analysis, macroeconomic

[18] I acknowledge that wages are endogenous when included in the regression equation, making the coefficient of wage inconsistent. However, this does not affect the consistency of the housing price coefficient, provided the instrumental variable is valid—i.e., uncorrelated with the residual conditional on wage and other control variables. The literature typically assumes that such conditional mean independence of the error term is sufficient for a causal interpretation of coefficients. This interpretation, however, relies on the assumption that the conditional mean of the error term is linear in the control variables, a standard assumption in the literature (Stock and Watson, 2020). If nonlinearity is a significant issue and the relationship between the independent variable of interest and control variables is not linear, the coefficient may be inconsistent (Frölich, 2008). Given that the results are robust to the inclusion of macroeconomic conditions and that nonlinearity concerns are typically assumed away in standard econometric handbooks (Stock and Watson, 2020), I do not consider potential nonlinearity a major threat to the validity of the results.

Table C.1: Robustness: Macroeconomic Control Variables

	(1) Migration	(2) Migration	(3) Migration	(4) Migration	(5) lnIncome	(6) lnIncome	(7) lnIncome	(8) lnIncome
FatherEduy× HPgap	0.011***	0.011***	0.009***	0.009***	0.021**	0.022**	0.027***	0.027***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.009)	(0.009)	(0.010)	(0.010)
HPgap	-1.064***	-0.779**	-0.947***	-0.699**	-2.720**	-2.770*	-3.009**	-2.981**
	(0.289)	(0.303)	(0.280)	(0.297)	(1.327)	(1.510)	(1.351)	(1.518)
Eduy× HPgap			0.009***	0.008***			-0.016	-0.016
			(0.003)	(0.003)			(0.013)	(0.013)
Macroeconomic Controls	-	√	-	√	-	√	-	√
FatherEduy× birthyearFE	√	√	√	√	√	√	√	√
K-P F-stat	43.241	37.685	29.381	25.508	62.223	44.568	41.908	30.220
LM test	80.792	67.772	82.021	68.667	107.637	85.255	110.246	86.392
Obs.	14,976	14,976	14,976	14,976	12,068	12,068	12,068	12,068
Mean(Dep. Var.)	0.202	0.202	0.202	0.202	9.798	9.798	9.798	9.798

NOTE: This table presents robustness results with and without macroeconomic control variables. Even-numbered columns exclude macroeconomic controls, while odd-numbered columns include them. Columns (2), (4), (5), and (7) are the estimates in the main results Table 1 and Table 2. Standard errors are clustered at prefecture times birth year level; ***p<0.01, **p<0.05, *p<0.1.

controls are included for migration outcomes to address potential omitted variable bias but excluded for income outcomes to avoid bad control issues.

D Appendix: Procedure of Imputation

The imputation takes the following steps. First, I use CHFS 2015 data, restrict the sample to males, and estimate the following equation:

$$ln(Income)_i = \alpha_0 + \alpha_1 Age_i + \alpha_2 Age\_squared_i + X_i' \alpha_X + \epsilon_i \tag{16}$$

X is a set of demographic and socioeconomic variables, including fixed effects for education, *Hukou* type, Communist party membership, job position, and birth cohort. There is also a coastal dummy, which accounts for regional differences.[19] Then, based on Equation (16), I calculate the predicted income for my main sample by applying the estimated coefficients to the available information on their fathers' characteristics.[20]

To evaluate the goodness of the imputation, I compare my estimates of the intergenerational income elasticity (IGE) to the existing literature. I show results in Appendix Table B.11 where the $FatherIncome \times birthyear$ fixed effects are dropped so that I observe the estimated coefficient of fathers' log income, i.e., the estimates of IGE. My IGE estimate is approximately 0.384, closely aligning with Fan et al. (2021), who report an IGE of 0.390 for the 1970-1980 birth cohort and 0.442 for the 1981-1988 birth cohort.[21]

[19] Communist party membership is an indicator of whether the father is a member of the Communist Party. Job position refers to administrative levels including 1) ordinary worker, 2) department manager, 3) general manager, 4) (deputy) team leader/section chief, 5) (deputy) division head, 6) (deputy) director, 7) (deputy) bureau head and above, 8) village cadre, 9) township cadre, etc. The coastal dummy equals one if the residential province was a coastal province when the child was age 14. For the birth cohort, I separate fathers into 10-year age groups based on their birth years. When the father's birth year is not available, I use the average birth year of fathers given the child's birth year, which I generated using the 2013 China Health and Retirement Longitudinal Study (CHARLS) data, a nationally representative dataset focusing on the old population.

[20] I do not use the coefficients of age, age squared, or birth cohort because I am using a cross-sectional dataset to impute fathers' income and want to avoid income variation caused by age differences. Instead of excluding age-related variables, an alternative approach involves constructing the imputed income for a worker at a representative age. This alternative approach involves calculating the imputed income under the assumption that all individuals are at the mean age, effectively adding a constant to all observations. The results will be the same, as the imputed income of fathers is centered (demeaned) before estimating the regression models. I also check the results incorporating age-related variables when imputing income, and they remain robust.

[21] The measurement and sample period in my study differ slightly from Fan et al. (2021). They use imputed parents' income rather than fathers' income and focus on individuals born between 1970-1988, while my sample includes individuals born between 1962-2000.

E Appendix: Solving for the Counterfactuals

I use iteration to obtain counterfactuals. Specifically, from the estimation above, I derive the estimates for parameters $\beta^d, \beta^r, \beta^w, \beta^h_{fedu\_L}, \beta^h_{fedu\_H}$ and fixed effects $\{\mu_p\}$ and $\{\pi_{fedu,t}\}$. $\{\xi_{fpt}\}$ and $\{\varepsilon_{pt}\}$ for all the prefectures and birth cohorts are calculated using the following equations:

$$\xi_{fpt} = \delta^{fedu}_{pt} - (\beta^w w_{pt} + \beta^h_{fedu\_L} h_{pt} + \beta^h_{fedu\_H} h_{pt} + \mu_p + \pi_{fedu,t})$$

$$\varepsilon_{pt} = h_{pt} - \Gamma(lnL_{pt} + w_{pt})$$

With the estimated parameters, fixed effects, and data on worker characteristics and prefectures, the counterfactual equilibrium is obtained through the following steps:

1. I denote the set of labor supply, housing prices, and prefecture average attractiveness for all the prefectures and birth cohorts as $\{L^0_{pt}\}$, $\{h^0_{pt}\}$, and $\{\delta^0_{fpt}\}$.

2. Increase the housing prices of the prefectures of interest, e.g., Beijing, by 10% via increasing the $\varepsilon_{Beijing}$, capturing changes in the housing supply regulations. Alternatively, I could decrease the housing prices faced by children of low-education fathers by 10%, representing a housing substitution policy.

3. Change in $\varepsilon_{Beijing}$ leads to change in housing price $h_{Beijing}$, which then leads to change in Beijing's attractiveness as a residential prefecture $\delta^{fedu}_{Beijing}$, and eventually affect L_p for all the prefectures, as workers change the migration destinations from Beijing to other prefectures. I denote these new labor supplies in different destinations $\{L^1_{pt}\}$.

4. Changes in labor supply will then change the housing prices in the housing market according to Equation (13). A decrease in labor supply in Beijing decreases its housing prices and vice versa for prefectures other than Beijing. A new set of housing prices $\{h^1_{pt}\}$ can be obtained by inserting $\{L^1_{pt}\}$, $\{w_{pt}\}$ and $\{\varepsilon_{pt}\}$ into Equation (13).

5. Changes in housing prices will then change the attractiveness of the prefectures according to Equation (10). A new set of attractiveness $\{\delta^1_{fpt}\}$ can be obtained by inserting $\{h^1_{pt}\}$, $\{w_{pt}\}$, $\{\mu_{pt}\}$, $\{\pi_{fedu,t}\}$, and $\{\xi_{fpt}\}$ into Equation (10).

6. Changes in attractiveness $\{\delta^1_{fedu,pt}\}$ of the destinations will affect labor supply again. A new set of labor supply $\{L^2_{pt}\}$ can be obtained by inserting $\{\delta^1_{fedu,pt}\}$

into Equation (12).

7. I then compare $\{L_{pt}^1\}$ and $\{L_{pt}^2\}$. If they are close enough, I stop the loop and claim I have reached a new equilibrium. Otherwise, I keep iterating Steps 4-6 until the two subsequent labor supplies $\{L_{pt}^s\}$ and $\{L_{pt}^{s+1}\}$ are close enough.