

# Housing Prices, Internal Migration, and Intergenerational Mobility

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- However, housing prices have been surging, particularly in high-income areas
  - “We have no home where there is work, and there is no work where there is home.”
  - Anecdotal evidence from a Chinese social media

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- The high housing costs may affect migration decisions differently for individuals from advantaged and disadvantaged backgrounds
  - Housing is a major component of migration costs
  - Young adults from disadvantaged families face restrictions, making them more affected by housing costs, which hinder migration and limit their ability to earn higher incomes

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  - Housing is a major component of migration costs
  - Young adults from disadvantaged families face restrictions, making them more affected by housing costs, which hinder migration and limit their ability to earn higher incomes
- This may reinforce existing inequalities and decrease intergenerational mobility

## This paper

- This paper examines how housing affordability affects intergenerational mobility in China by influencing internal migration

Housing costs  $\uparrow \Rightarrow$  workers from disadvantaged families migrate less and earn lower income  
 $\Rightarrow$  parental background becomes a stronger determinant of individuals' income  
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- A spatial equilibrium model for policy experiments

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Note:

- “Children” refers to adult children who are young adults when making migration decisions
- Both the effects on migration and income are explored
- “Advantaged” or “disadvantaged” refers to the parental background of the individuals

## Intuitively, this is true; why do we need a paper?

The direction of the impact is theoretically ambiguous:

- Rising housing prices place a greater financial burden on low-income families  
→ Larger responses from individuals with **disadvantaged** backgrounds
- Disadvantaged young adults 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

→ Larger responses from children with **advantaged** backgrounds

We need empirical analysis to determine which force dominates



## Preview of Findings of the Reduced-Form Analysis

- Higher housing costs decrease migration and income  
... but fathers' education mitigates these impacts
- Adult children from disadvantaged families are more affected by housing costs  
→ less migration → lower income  
Housing costs  $\uparrow \Rightarrow$  importance of parental backgrounds  $\uparrow \Rightarrow$  intergenerational mobility  $\downarrow$
- A 10% increase in destination housing prices raises intergenerational persistence by 12%

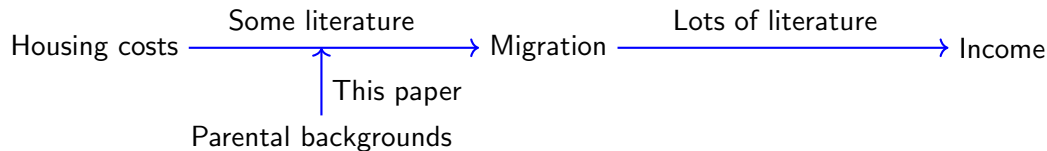
# Preview of Findings of the Structural Analysis

Structural analysis suggests the heterogeneity depends on the nature of the destination

- Rent subsidies to migrants in megacities increase migration more among advantaged children  
→ exacerbating income disparities
- Policies that either 1) target disadvantaged children or 2) offer non-targeted subsidies in non-megacities increase migration for disadvantaged children  
→ improve intergenerational mobility

Such differences across destinations have important policy implications

## Relation to the Literature



- This implies housing costs are a crucial determinant of intergenerational mobility
  - Few causal determinants have been established in the literature

# Literature Review

- Determinants of intergenerational mobility (e.g. Parman, 2011; Feigenbaum, 2015; Olivetti and Paserman, 2015; Zheng and Graham, 2022)  
→ Propose a new determinant in a developing context
- Driving forces of internal migration (e.g. Bazzi, 2017; Cai, 2020)  
→ Focus on heterogeneous impacts that affect social mobility
- The Moving to Opportunity (MTO) experiment (e.g. Chetty et al., 2016)  
→ Propose a different age range to break the influence of parental background

# Roadmap

- 1 Data and Empirical Strategy
- 2 Reduced-Form Results
- 3 Spatial Equilibrium Model
- 4 Conclusion

# Data

- China Household Finance Survey (CHFS) 2017, nearly nationally representative survey
  - Migration history
  - Parents information, regardless of whether they live together
  - Demographics and income, including income for agricultural and informal sectors

## Sample:

- Individuals aged 17-55, both men and women, from non-Tier 1 prefectures
  - Adult children who report information about their parents
- CEIC database, annual data for each prefecture, 2000-2017
  - Selling prices for residential properties
    - in log yuan per square meter, adjusted to 2000 RMB using the national CPI
    - Data imply that rents are highly correlated with housing prices
  - Local economic conditions
- Census samples 2000 and the China Migrants Dynamic Monitoring Survey (CMDS)

# Measuring Relevant Housing Prices

Goal: Measure housing prices relevant to migration across destinations and over time

- Weighted average across potential destinations
- Use the gap between destination and origin
- Aggregate housing price gaps into a single lifetime measure

# Measuring Relevant Housing Prices

For an individual from origin prefecture  $o$  born in year  $t$  of age  $l$ :

$$HPgap_{ot} = \sum_{k=16}^{\min\{l,45\}} a_k \times \left( \sum_{d \neq o} w_{od} Inprice_{d,t+k} - Inprice_{o,t+k} \right) / \sum_{k=16}^{\min\{l,45\}} a_k$$

Weights are generated using the 2000 census for years before the sample period

$\text{Mean}(HPgap) = .55$ , meaning that  $HP_{dest}$  is about 173% of  $HP_{orig}$

► Figure

► Numerical Example


► Migration Weights



# Measuring Relevant Housing Prices

For an individual from origin prefecture  $o$  born in year  $t$  of age  $l$ :

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$$a_k = \frac{\# \text{ of people migrated at age } k}{\# \text{ of migrants}}$$

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# Empirical Strategy

## ► Chinese Prefectures

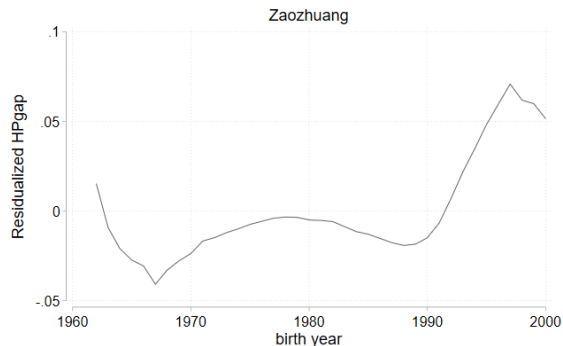
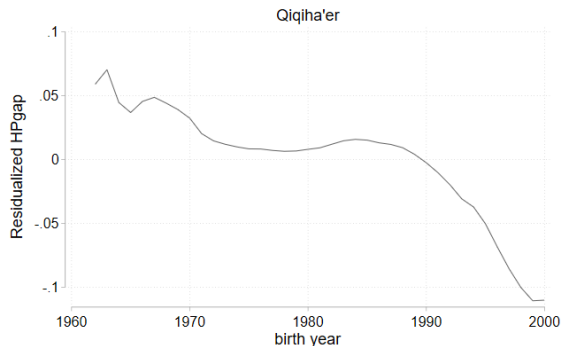
For individual  $i$  born in year  $t$  with origin prefecture  $o$ :

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

*Outcome* is an indicator for migration or the log of income

## Variation for Estimation

- Children from the same origin prefecture but born in different years face different housing price shocks during key migration decision ages.
- Children from different origin prefectures face different housing price shocks given the different origin and destination prefectures.

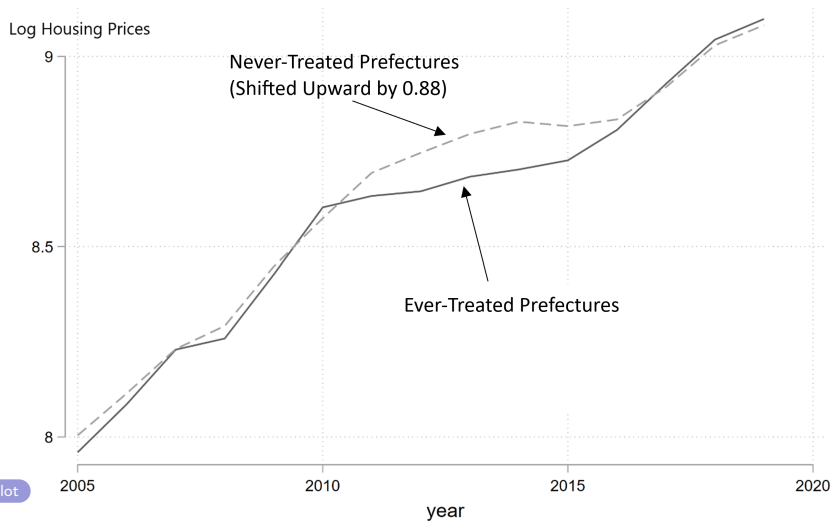


# Instrumental Variable: Housing Purchase Restriction (HPR) policy

- This policy was launched in 46 prefectures across China from late 2010 to early 2011
- The general framework was to restrict households to owning no more than two properties.
- Since 2014, the policy has begun to be removed.
- This policy has been used in many existing papers as an unexpected shock on housing prices (Chen et al., 2017; Zhao and Zhang, 2022; Liu et al., 2023)

► Policy Dates

# Housing Prices for Ever-Treated and Never-Treated Prefectures



► Event Study Plot

# Instrumental Variable Construction

- Create a prefecture-year dummy variable indicating whether the Housing Purchase Restriction policy is in effect
- Calculate the weighted average in the same way as for housing prices
- The weighted average of policy implementation is used as the IV for the housing price gap
- The 1st stage coefficient is expected to be negative, as the policy reduced housing demand and slowed price growth

► Shift-Share IV

# Migration Results

	Migration			
	OLS (1)	IV (2)	IV (3)	IV (4)
FatherEduy	0.005*** (0.001)	0.005*** (0.001)		
FatherEduy $\times$ HPgap	0.009*** (0.001)	0.011*** (0.002)	0.011*** (0.002)	0.009*** (0.002)
HPgap	-0.252*** (0.073)	-0.753*** (0.292)	-0.779** (0.303)	-0.699** (0.297)
Eduy $\times$ HPgap	-	-	-	Y
FatherEduy $\times$ birthyearFE	-	-	Y	Y
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

A 10 p.p. increase in *HPgap* decreases migration probability by 7 p.p., 35% of the mean rate

A 10 p.p. increase in *HPgap* raises the influence of fathers' education on children's migration by 18%



## Income Results

	lnIncome			
	OLS (1)	IV (2)	IV (3)	IV (4)
FatherEduy	0.023*** (0.004)	0.023*** (0.004)		
FatherEduy $\times$ HPgap	0.028*** (0.006)	0.022** (0.010)	0.021** (0.009)	0.027*** (0.010)
HPgap	-0.795** (0.334)	-2.852** (1.288)	-2.720** (1.327)	-3.009** (1.351)
Eduy $\times$ HPgap	-	-	-	Y
FatherEduy $\times$ birthyearFE	-	-	Y	Y
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: Macroeconomic conditions are not controlled in this table as they are bad controls

A 10 p.p. increase in *HPgap* increases intergenerational persistence by 12%

# Robustness Check

- “Market access”-type weights [▶ Results](#)
- Control for  $\text{originFE} \times \text{BirthyearFE}$  [▶ Results](#)
- Additional macroeconomics controls [▶ Results](#)
- Control for non-housing cost of living [▶ Results](#)
- Subsamples [▶ Results](#)
- Use average income from multiple waves [▶ Results](#)
- Impute fathers' income and household assets [▶ Results](#)
- Alternative housing prices dataset [▶ Results](#)

[▶ Additional Robustness Results](#)

# Which levels of education matter most?

1) No schooling (32%), 2) primary school (33%), 3) junior high school (19%), 4) senior high or above (16%).

The variables are constructed to reflect the impact of each **additional** level of education

	OLS		IV	
	(1) Migration	(2) lnIncome	(3) Migration	(4) lnIncome
1{FatherEduLevel $\geq$ 2} $\times$ HPgap	0.045*** (0.011)	0.130* (0.069)	0.073*** (0.019)	0.205* (0.115)
1{FatherEduLevel $\geq$ 3} $\times$ HPgap	0.027* (0.015)	0.092 (0.069)	0.018 (0.022)	0.132 (0.090)
1{FatherEduLevel $\geq$ 4} $\times$ HPgap	-0.000 (0.019)	-0.020 (0.076)	0.009 (0.025)	-0.036 (0.102)
HPgap	-0.297*** (0.073)	-0.811** (0.347)	-0.668** (0.303)	-2.863** (1.363)
FatherEduLevelFE $\times$ birthyearFE	Y	Y	Y	Y
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

## Rural vs Urban

	Rural		Urban	
	(1)	(2)	(3)	(4)
	Migration	lnIncome	Migration	lnIncome
FatherEduy $\times$ HPgap	0.012*** (0.003)	0.044** (0.014)	0.006 (0.004)	-0.013 (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

► Descriptive Stats

► Agricultural Employment

► Gender Heterogeneity

# Structural Model

- Migration decision is not just a binary choice. It also involves selecting from a choice set
  - Beijing's high housing prices can make workers
    - stay in their origin
    - migrate to a cheaper city
  - I capture this complexity by modeling migration decisions as a set of discrete choices
- To further explore policy implications, I build a bare-bones spatial equilibrium model to take into account general equilibrium effects and analyze counterfactuals

# Overview of the Model

- Labor Market
  - Workers decide where to live based on the prefecture's housing prices, economic conditions, distance from origin, and personal preferences.
- Housing Market
  - Housing demand is affected by population size
  - Housing supply depends on geographical factors, regulations, and other local characteristics

# Labor Market

The utility that a worker  $i$  with parental background  $f$  from origin  $o$  born in year  $t$  obtains by choosing to live in prefecture  $p$  is given by:

$$U_{ifopt} = \delta_{fpt} + \chi_{iop} + \epsilon_{ifopt}$$

where

$$\delta_{fpt} = \beta_f^h h_{pt} + \theta g_{pt} + \mu_p + \pi_{ft} + \xi_{fpt}$$

$$\chi_{iop} = \beta^d \ln \text{Distance}_{op} + \beta^r \text{rural}_i \times 1\{o \neq p\} + \beta^m \text{male}_i \times 1\{o \neq p\}$$

$\epsilon_{ifopt}$  is drawn from a standard Type I Extreme Value distribution, which captures idiosyncratic tastes for prefectures

The origin prefecture is also an option

Worker  $i$  choose to live in  $p$  if  $U_{ifopt} > U_{ifodt}$  for  $\forall d \neq p$

The probability that worker  $i$  choose to live in prefecture  $p$  is:

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

The model is estimated in two steps:

- The probability equation is estimated using MLE. Obtain  $\{\hat{\delta}_{fpt}\}$ , which are at father's education  $\times$  prefecture  $\times$  birth year level
- Estimate  $\hat{\delta}_{fpt} = \beta_f^h h_{pt} + \theta g_{pt} + \mu_p + \pi_{ft} + \xi_{fpt}$  using 2SLS
  - As residual  $\xi_{fpt}$  includes amenities which is correlated with housing prices  $h_{pt}$ , I use Housing Purchase Restriction policy to instrument housing prices



In practice, there is not enough data to estimate  $\delta_{fpt}$  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.

$$\begin{aligned}\hat{\delta}_{fpt} = & \beta_1 \text{FatherEduHigh}_f \times \text{HousingPrices}_{pt} + \beta_2 \text{HousingPrices}_{pt} \\ & + G'_{pt} \Theta + \mu_p + \pi_{ft} + \xi_{fpt}\end{aligned}$$

Table: Conditional logit

	OLS		IV	
	(1)	(2)	(3)	(4)
FatherEduHigh $\times$ HousingPrices	0.380*** (0.107)	0.384*** (0.110)	0.747** (0.322)	0.758** (0.326)
HousingPrices	-1.181*** (0.347)	-1.011*** (0.376)	-4.050*** (1.230)	-3.606** (1.436)
FatherEduHigh $\times$ birthcohort FE	Y	Y	Y	Y
Prefecture FE	Y	Y	Y	Y
Controls	-	Y	-	Y
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

# Housing Market

After some math, making housing demand equals housing supply:

$$h_{pt} = \Gamma \ln L_{pt} + \varepsilon_{pt}$$

where  $\Gamma > 0$  and  $\varepsilon_{pt}$  depends on worker's preference for housing, price-to-rent ratio of housing, government land regulation, etc.  $\Gamma$  is calibrated based on the existing literature.

# Equilibrium

Equilibrium is defined by a menu of housing prices  $\{h_{pt}\}$  with populations  $\{L_{pt}\}$ , such that:

$$\begin{aligned} L_{pt} &= \sum_{i \in \mathcal{I}_t} w_i \cdot Pr(\text{worker } i \text{ choose to live in prefecture } p) \\ &= \sum_{i \in \mathcal{I}_t} w_i \cdot \frac{\exp(\delta_{fpt} + \chi_{iop})}{\sum_{n \in N} \exp(\delta_{fnt} + \chi_{ion})} \end{aligned} \quad (1)$$

where  $\delta_{fpt} = \beta_f^h h_{pt} + \theta g_{pt} + \mu_p + \pi_{ft} + \xi_{fpt}$  and  $w_i$  is the survey weight for the individual

$$h_{pt} = \Gamma \ln L_{pt} + \varepsilon_{pt} \quad (2)$$

# Counterfactual Analysis of Migration Responses to Rent Subsidy Policies

FatherEdu	Change in Percentage Points (%)		
	Stay	Migrate to Tier-1	Migrate to Non-Tier-1
<i>Panel A: 10% Rent Subsidy in Tier-1 Prefectures</i>			
L	-0.79	1.01	-0.22
H	-1.20	1.70	-0.49
<i>Panel B: 10% Rent Subsidy in Tier-1 Prefectures for Migrants with Low-Education Fathers</i>			
L	-0.92	1.18	-0.26
H	0.23	-0.29	0.06
<i>Panel C: 10% Rent Subsidy in Non-Tier-1 Prefectures</i>			
L	-3.25	-0.21	3.46
H	-2.35	-0.49	2.84

For interpretation, the -0.79 percentage point change in Panel A reflects a reduction in the proportion of workers with low-education fathers remaining in their origin prefecture, from 85.15% to 84.36%.

# Impacts on intergenerational mobility

	Income Gap (High vs. Low Edu Fathers)
<i>Panel A:</i> 10% Rent Subsidy in Tier-1 Prefectures	+3%
<i>Panel B:</i> 10% Rent Subsidy in Tier-1 Prefectures for Migrants with Low-Education Fathers	-13%
<i>Panel C:</i> 10% Rent Subsidy in Non-Tier-1 Prefectures	-4%

# Take Aways

- High housing costs significantly deter internal migration, especially for children from less privileged backgrounds
- This reinforces economic disadvantage and reduces intergenerational mobility
- In China, with its geographical inequality and low intergenerational mobility, affordable housing policies could address both issues by promoting internal migration
- Policy design must account for the nature of the destination

# The End

Thank you for listening!

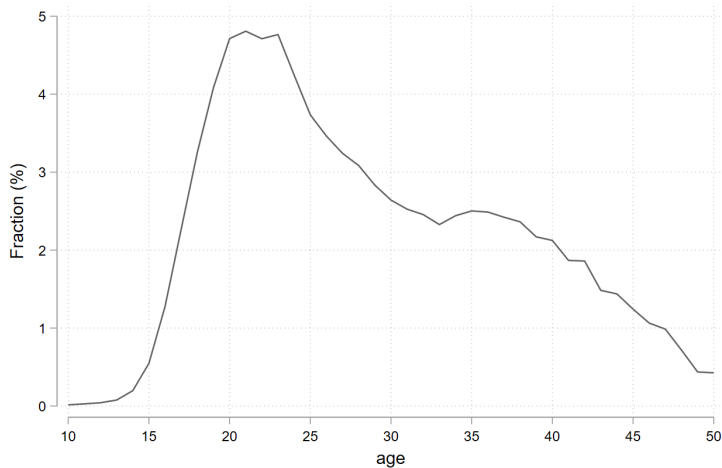


# Map of 334 Chinese Prefectures



A prefecture can have both rural and urban areas [▶ Back](#)

# Age-specific Migration Probability



► Back

## Migration Enters Both Sides

For an individual from origin prefecture  $o$  born in year  $t$ :

$$Migration_{iot} = \beta \sum_p w_{op} HP_{dest_{pt}} + \text{other terms}$$

but  $w_{op}$  is constructed based on historical migration stock, which itself affects migration

To address this concern:

- Time-invariant factors should be controlled by origin FE, including  $\sum_p w_{op} \overline{HP_{dest_p}}$ 
  - $\beta$  captures the impact of changes in HP weighted by the importance of the destination
- “Market access”-type weights which depend only on destination GDP and the distance between origin and destination
- $w_{op}$  is not used for the discrete choice model

## Numerical Example of Housing Price Gap Construction

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

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# Descriptive Statistics

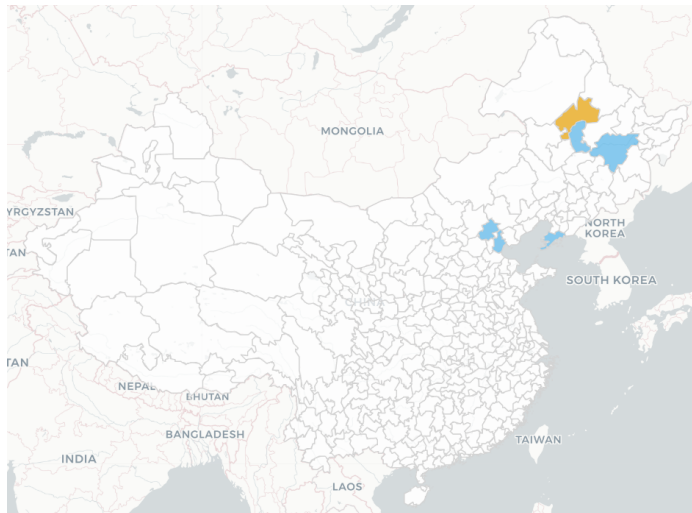
	Mean	SD
Migration	0.20	0.40
lnIncome	9.80	1.67
FatherEduy	5.74	4.51
HPgap	0.51	0.51
Male	0.46	0.50
Eduy	10.05	3.75
Rural Hukou	0.67	0.47
Age	43.19	8.95

▶ Back

# 1{Ever Migrate}

	OLS		IV	
	(1)	(2)	(3)	(4)
FatherEduy	0.005*** (0.001)	0.005*** (0.001)		
FatherEduy × HPgap	0.007*** (0.001)	0.008*** (0.002)	0.009*** (0.002)	0.007*** (0.002)
HPgap	-0.242*** (0.086)	-1.288*** (0.425)	-1.207*** (0.428)	-1.123*** (0.417)
Eduy × HPgap	-	-	-	Y
FatherEduy × birthyearFE	-	-	Y	Y
K-P F-stat		23.664	22.882	15.572
LM test		43.347	42.588	43.412
Obs.	13,859	13,859	13,859	13,859
Mean(Dep. Var.)	0.254	0.254	0.254	0.254

## Top 5 destinations of Qiqiha'er



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



- The IV has a shift-share structure.
- A linear shift-share IV is valid as long as either the share is exogenous or the shift is exogenous. (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022)
- In this paper, identification comes from the shift, the sudden and unexpected nature of the Housing Price Restriction policy and the resulting decreases in demand.

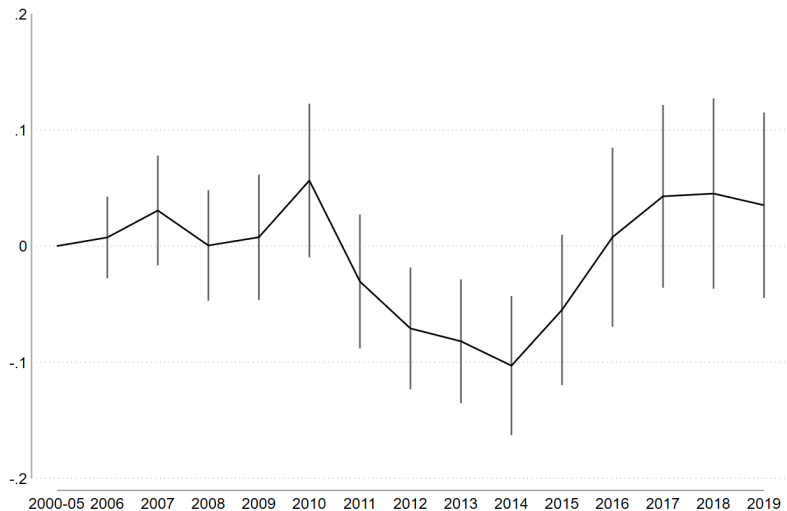
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Table: IV Results: First Stage

	(1)	(2)	(3)	(4)	(5)	(6)
	HPgap	FatherEduy × HPgap	HPgap	FatherEduy × HPgap	HPgap	FatherEduy × HPgap
HPR	-0.165*** (0.014)	4.465*** (0.393)	-0.161*** (0.014)	3.049*** (0.438)	-0.163*** (0.014)	3.166*** (0.434)
FatherEduy × HPR	0.001** (0.001)	2.291*** (0.060)	0.000 (0.001)	2.647*** (0.057)	-0.000 (0.001)	2.709*** (0.057)
FatherEduy × birthyearFE	-	-	Y	Y	Y	Y
Eduy × birthyearFE	-	-	-	-	Y	Y
Obs.	14,976	14,976	14,976	14,976	14,976	14,976
Adj. R-sq	0.995	0.456	0.995	0.494	0.995	0.495

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# Housing Purchase Restriction Policy Event Study Plot



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## “Market access”-type weights

	Migration				lnIncome			
	OLS	IV			OLS	IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FatherEduy	0.005*** (0.001)	0.004*** (0.001)			0.022*** (0.003)	0.022*** (0.003)		
FatherEduy × HPgap	0.008*** (0.001)	0.011*** (0.002)	0.011*** (0.002)	0.008*** (0.002)	0.026*** (0.007)	0.022** (0.011)	0.023** (0.010)	0.021* (0.011)
HPgap	-0.263*** (0.075)	-1.413*** (0.502)	-1.489*** (0.528)	-1.341*** (0.509)	-0.885** (0.346)	-1.908 (1.580)	-1.703 (1.695)	-1.640 (1.756)
Eduy × HPgap	-	-	-	Y	-	-	-	Y
FatherEduy × birthyearFE	-	-	Y	Y	-	-	Y	Y
K-P F-stat		15.298	14.035	9.330		40.993	36.446	23.966
LM test		30.837	28.652	28.657		75.903	68.583	68.692
Obs.	15,601	15,601	15,601	15,601	12,570	12,570	12,570	12,570
Mean(Dep. Var.)	0.200	0.200	0.200	0.200	9.794	9.794	9.794	9.794

$w_{op} = \log\left(\frac{GDP}{distance}\right)$ . Use prefecture-level GDP in 1999 from CEIC and distance from Baidu Maps.

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## Additional Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Migration	Migration	Migration	Migration	lnIncome	lnIncome	lnIncome	lnIncome
FatherEduy× HPgap	0.010*** (0.002)	0.009*** (0.002)	0.009*** (0.002)	0.006** (0.003)	0.033*** (0.011)	0.036*** (0.012)	0.022* (0.012)	0.029** (0.012)
HPgap			-0.716** (0.291)	-0.656** (0.286)			-0.562 (1.552)	-0.718 (1.552)
Eduy× HPgap		0.004 (0.004)		0.009*** (0.003)		-0.012 (0.017)		-0.022 (0.014)
OriginFE× BirthyearFE	Y	Y	-	-	Y	Y	-	-
Interaction terms	-	-	Y	Y	-	-	Y	Y
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

Fiscal expenditure, foreign direct investment (FDI), exports, GDP growth rate, and their interactions with fathers' years of education.

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Table: Robustness: Control for non-housing cost of living

	(1)	(2)	(3)	(4)
	Migration	Migration	lnIncome	lnIncome
FatherEduy× HPgap	0.010*** (0.002)	0.007*** (0.002)	0.020* (0.010)	0.026** (0.011)
HPgap	-0.769** (0.317)	-0.695** (0.311)	-2.300 (1.514)	-2.615* (1.529)
FatherEduy× COL	0.000** (0.000)	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)
COL	0.012* (0.006)	0.012* (0.006)	0.029 (0.026)	0.029 (0.026)
Eduy× HPgap		0.008*** (0.003)		-0.017 (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

Table: Robustness: Sample Construction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Migration	Migration	Migration	Migration	lnIncome	lnIncome	lnIncome	lnIncome
FatherEdu × HPgap	0.010*** (0.003)	0.009*** (0.003)	0.011*** (0.003)	0.011*** (0.003)	0.024** (0.010)	0.022** (0.011)	0.024** (0.012)	0.026** (0.012)
HPgap	-0.989** (0.457)	-1.220** (0.538)	-0.957** (0.451)	-0.965** (0.458)	-3.388** (1.700)	-3.754** (1.779)	-2.816* (1.651)	-3.278* (1.821)
Exclude	-	adjacent to Tier-1	high GDP per capita	popular destinations	-	adjacent to Tier-1	high GDP per capita	popular destinations
Obs.	15,128	14,408	14,677	14,200	12,189	11,621	11,839	11,422
Mean(Dep. Var.)	0.201	0.202	0.205	0.210	9.793	9.782	9.770	9.745

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Table: Robustness: Average Income Across Waves

	(1)	(2)	(3)	(4)
	lnIncome	lnIncome	lnIncome multi-year	lnIncome multi-year
FatherEduy × HPgap	0.021** (0.009)	0.027*** (0.010)	0.022*** (0.008)	0.027*** (0.009)
HPgap	-2.720** (1.327)	-3.009** (1.351)	-3.082** (1.240)	-3.349*** (1.256)
Eduy × HPgap		-0.016 (0.013)		-0.014 (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



## Residualized Fathers' Education

	(1)	(2)	(3)	(4)
	Migration	Migration	lnIncome	lnIncome
FatherEduy <sub>r</sub> × HPgap	0.009*** (0.002)	0.008*** (0.002)	0.024** (0.012)	0.027** (0.012)
HPgap	-0.818*** (0.315)	-0.818*** (0.315)	-2.493* (1.392)	-2.474* (1.392)
Eduy × HPgap		0.002 (0.004)		-0.014 (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

## Alternative Housing Price Dataset

	(1)	(2)	(3)	(4)
	Migration	Migration	lnIncome	lnIncome
FatherEduy $\times$ HPgap	0.011*** (0.002)	0.008*** (0.002)	0.025** (0.010)	0.036*** (0.011)
HPgap	-1.738*** (0.564)	-1.559*** (0.542)	-4.146* (2.203)	-5.226** (2.291)
Eduy $\times$ HPgap		0.009*** (0.003)		-0.034** (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

## Impute Fathers' Income

	(1)	(2)	(3)	(4)	(5)	(6)
	Migration	Migration	Migration	lnIncome	lnIncome	lnIncome
lnFatherIncome	0.085*** (0.013)			0.381*** (0.059)		
lnFatherIncome × HPgap	0.162*** (0.036)	0.185*** (0.034)	0.138*** (0.037)	0.311* (0.167)	0.355** (0.150)	0.437*** (0.165)
HPgap	-0.852*** (0.294)	-0.868*** (0.304)	-0.770*** (0.297)	-3.107** (1.267)	-2.775** (1.299)	-3.069** (1.330)
Eduy × HPgap	-	-	Y	-	-	Y
lnFatherIncome × birthyearFE	-	Y	Y	-	Y	Y
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

Table: Heterogeneity: Male vs Female

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
	Migration	lnIncome	lnIncome of Spouse	Migration	lnIncome	lnIncome of Spouse
FatherEduy × HPgap	0.007** (0.003)	0.027* (0.014)	0.014 (0.016)	0.010*** (0.003)	0.017 (0.013)	0.021* (0.011)
K-P F-stat	18.498	35.181	29.568	24.610	35.156	32.658
LM test	53.194	94.607	84.093	65.849	93.409	89.168
Obs.	6,829	6,039	4,619	8,147	6,029	6,252
Mean(Dep. Var.)	0.196	10.113	9.634	0.204	9.480	10.113

## Additional Robustness Check

- Residualized fathers' education [▶ Results](#)
- Control for FatherEduy  $\times$  Ever-treated [▶ Results](#)
- Use region-specific CPI [▶ Results](#)

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Table: Robustness: IV Ever-treated

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Migration	Migration	Migration	Migration	lnIncome	lnIncome	lnIncome	lnIncome
FatherEduy × HPgap	0.011*** (0.002)	0.011*** (0.002)	0.009*** (0.002)	0.008*** (0.002)	0.021** (0.009)	0.020* (0.010)	0.027*** (0.010)	0.025** (0.011)
HPgap	-0.779** (0.303)	-0.775** (0.303)	-0.699** (0.297)	-0.695** (0.297)	-2.720** (1.327)	-2.721** (1.328)	-3.009** (1.351)	-3.010** (1.352)
Eduy × HPgap			0.008*** (0.003)	0.008*** (0.003)			-0.016 (0.013)	-0.016 (0.013)
FatherEduy × Evertreated		0.002 (0.006)		0.003 (0.006)		0.010 (0.029)		0.009 (0.029)
K-P F-stat	37.685	37.724	25.508	25.542	62.223	62.196	41.908	41.893
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

## Adjust income using province $\times$ urban/rural CPI

	(1)	(2)
	lnIncome	lnIncome
FatherEdu $\times$ HPgap	0.018** (0.009)	0.025** (0.010)
HPgap	-2.217* (1.305)	-2.600* (1.328)
Edu $\times$ HPgap		-0.021 (0.013)
FatherEdu $\times$ birthyearFE	Y	Y
K-P F-stat	62.346	42.009
LM test	107.633	110.267
Obs.	11,958	11,958
Mean(Dep. Var.)	9.198	9.198

## Fathers' Education Level: Rural vs Urban

<b>Fedutype</b>	<b>Rural (%)</b>	<b>Urban (%)</b>
1	39.15	16.35
2	36.06	27.22
3	17.40	23.52
4	7.39	32.91

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# Impacts on Agricultural Employment

	Rural Sample	
	(1)	(2)
FatherEduy $\times$ HPgap	-0.006* (0.003)	-0.008** (0.003)
HPgap	1.031* (0.601)	1.105* (0.613)
Eduy $\times$ HPgap	-	Y
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

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