Local Land Allocation and Demographic Transitions across Time and Space in China

By Qiaohairuo Lin and Chunru Zheng*

This paper attributes the dramatic population decline in recent years in China as an unintended consequence of local governments' land allocation decisions, motivated by the novel industrial discounts in the land market. We construct a dynamic spatial-overlapping generation framework to capture the interplay of governments' land allocation, population controls, and public education expenditures on household family-planning decisions. In this model, compared with a free land market equilibrium, local governments tend to prioritize industrial land usage, aiming at a higher industrial output, while at the expense of lower fertility rates and real income. Estimating this model to match empirical distributions and conducting several counterfactual analysis, we find that: First, cities with higher productivities and amenities tend to disproportionately allocate more land to industrial use instead of residential use. Second, under the One Child Policy, the realized fertility rate in China was significantly below the fertility rate needed for the natural population replacement, yet shifting to a free land market could have potentially helped China address this fertility rate gap by 16.33%.

Keywords: Land Use, Fertility Rate, Education, Migration

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I. Introduction

In 2022, 9.56 million individuals were born in China, while 10.41 million died, resulting in a decline of 850,000 in population, and marking the first time since the early 1960s that the number of deaths has exceeded the number of births in China. This was the sixth consecutive year of declining population growth (Figure 1). This population decline happened ten years earlier than the government's official prediction, which could have far-reaching implications for the country's economy and social structure.[1] Therefore, there is a need for more analysis and understanding of the factors that contribute to the reluctance in fertility.

In contrast to the sharp decreasing fertility rate, house prices in China have been surging fast over the past decade. Housing privatization in China just started in 1998, yet since then, housing prices have increased nearly twice as fast as national income.[2] Moreover, in China's culture, parents are often expected to help out with the cost of purchasing an apartment for the newlyweds, which combined with the boy preference, has been shown to increase the savings rates in China and bid up housing price in urban areas (Wei and Zhang, 2011). According to the China Fertility Report in 2019, high housing costs are one of the most significant factors discouraging young people from having children, alongside other reasons such as the high costs of education, medical care, retirement burdens, and the opportunity cost of childbearing.[3]

In this paper, We connect the low fertility rate in China with the high housing price, and attributes it as an unintended consequences of governments' land allocation. This is motivated by the striking price gap between industrial and residential land. We observe two stylized facts from China's land transactions records: first, industrial lands are leased at an average discount of 47% compare to that of residential land. Moreover, this pro-industrial-land discount differs across cities, and is even larger in more developed coastal areas, indicating higher priority for industries in land allocation. Theorectically, in a general framework of Rosen-Roback fashion, We prove that to maximize worker welfare, residential land prices should be equal to or lower than industrial land prices. This suggests that the industrial land discount observed from the empirical datasets points to a potential land misallocation.

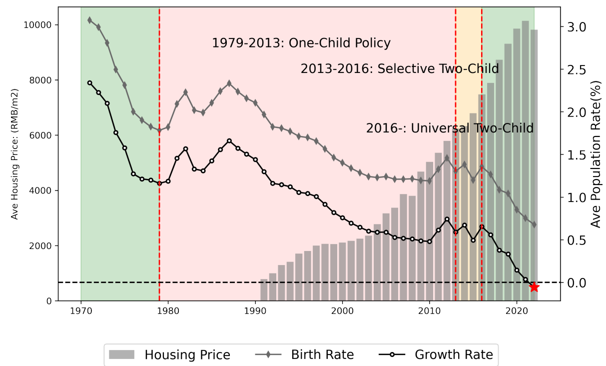
Intuitively, from the perspective of local governments, there exists a tradeoff between prioritizing land for industrial (for business) versus residential (for housing) purposes. While expanding industrial land may attract more firms,

[1]For instance, in 2019, the United Nations released the *"World Population Prospects (2019)"*, forecasting that China's population will reach its peak in 2031. Additionally, the China Academy of Social Science projected that China's population will begin to decline after 2029, eventually falling to 1.44 billion, as outlined in the *"Reports on China Population and Labor (2019)"*.

[2]Chen and Wen (2017) describe this as the puzzle of "real housing prices outpacing income" and interpret China's housing boom as a rational bubble that emerged naturally from the economic transition. For instance, rational expectations for a strong future demand for alternative stores of value can lead currently productive agents to speculate in the housing market.

[3]Zeping Ren, Chai Xiong, Zhe Zhou. (2019). The Approaching Demographic Crisis - China Fertility Report 2019, *Evergrande Wealth.* http://pdf.dfcfw.com/pdf/H3_AP201901041282086287_1.pdf

FIGURE 1. CHINA'S BIRTH RATE V.S HOUSING PRICE BY YEAR



Notes: Data Source: China Economic Statistics Yearbook 2022.

stimulating industrial growth with a reduced cost, this strategy could restrict the availability of residential land, which would push up housing prices and local living costs. [4] This process is similar to zoning policies in many other countries, where previous literature have discussed how land-use restrictions can escalate housing prices in big cities and impede the efficiency of labor reallocation across regions (Hsieh and Moretti, 2019; Gyourko and Molloy, 2015*a*). Urban land in China, institutionally owned and strictly regulated by local governments, provides me a unique opportunity to explore the impacts of Macro-level land policies on household decisions. The past three decades have seen rapid industrialization in China, which was based on the intentional land allocation reserved for industrial usage, and thus restricts space for residential houses.

We thus construct a dynamic spatial-overlapping generation (henceforth, OLG) framework to connect the fertility rate with the real housing price in China, attributing it to city-level variations in land allocation between industrial and residential purposes. Typically, previous literature delving into the effects of misallocation in the housing market would assume that the national aggregate labor is fixed, or take the population growth within an economy as given (Hsieh and Klenow, 2009; Gyourko and Molloy, 2015*a*). My work expands upon this body of literature by integrating population growth into a spatial model.

In this paper, We provide the first unified framework to explore the interactions between government land allocation, population control, and public education expenditure. First, "population control" in my framework refers to the "One-Child" policy in China, impletmented from 1970s to 2016. China is the only country that once used a stringent enforcement of the birth control nationalwhile, and so the

[4] Alongside the disparities in land lease prices, these statistics indicate the potential for severe housing affordability problems in big cities. For example, a recent study by Li, Qin and Wu (2020) recorded a mortgage payment-to-income ratio of 1.16 for the top 1% cities in China, which is much higher compared to cities like New York (0.31) and HongKong (0.87).

potential fertility willingness during this period would be constrained. To address this concern, We quantify the "One-Child" policy fine as a additional childrearing cost in my model for parents who aim to have a second child. Second, this project delves into households' family-planning decisions and their impacts on human capital dynamics over time and space. As the micro foundation, concerning "human capital," We assume that parents value both the number and future welfare of their children, guiding their investment in children's education. More specifically, the future welfare of children hinges on their educational attainment and location choices, and parents would rationally predict these decisions. This assumption is movited by the "education fever" in many East Asian countries, which has become another financial burden restricting fertility rates among the current generation (Kim, Tertilt and Yum, 2024). We incorparate this process as the "Quantity-Quality" trade-off in family-planning decisions. Extremely low fertility rates, combined with high housing costs and "education fever," are typical features in many developed countries, particularly in Japan, Korea, and several European countries. Therefore, the policy implications of this framework could be applicable to many other countries.

In this model, individuals live for two periods: childhood and adulthood. Childhood education, categorized into higher and lower levels, determines their future skill types as either skilled or unskilled workers. At the end of each period, children relocate based on their expected welfare, and then transition into the next period as adults. Significant decisions, including consumption, housing, and family planning–that is, the number of children and their educational investment–are made during adulthood. Parents' family planning utility comes from both the preference for having more children, and the anticipated utility of their children in the future. More specifically, the future welfare of children hinges on their educational attainment and location choices, and parents would rationally predict these decisions, deciding their investment in children's education. This dynamic is referred to as the "Quantity-Quality" trade-off.

We then compare the outcomes of this model with a theoretical baseline where land allocation is determined by market forces. In this theoretical environment, governments lack the authority to allocate, and instead, landlords in a competitive land market would maximize the revenues from selling the land with a flexibility to adjust their usages. Eventually, the unit price of both types of land should be equal to each other. Under this circumstance, We find that efficient land allocation depends on three factors: land intensity in the production function, housing share in the expenditure, and household preference for childrearing. Comparing the outcomes of this equilibrium with real-world data from China's land market in 2010, We find that in the reality, local governments tend to allocate more land to industrial use, aiming at higher industrial outputs. However, this allocation comes at the cost of a lower fertility rate and household welfare. This comparison highlights the trade-off between the interests of firms and workers in urban land allocation decisions.

Since productivity and amenities cannot be observed directly in the data, We calibrate the model to data on land allocation, industrial output and population distribution from year 2010 at the city level. Specially, We target the moments of the industrial output in each city to calibrate city productivity; and to calibrate city amenities, We match the population distribution for both skilled and unskilled workers. Then, with the productivity and amenities variables calibrated, We revisit the stylized facts presented in the empirical section. First, We find that cities with higher calibrated productivity tend to prioritize industrial land usage, which supports the claim that *developed regions experience wider price gaps between industrial and residential land.* Second, We also find the estimated fertility rates from the model show a negative correlation with the share of industrial land, confirming the third stylized fact that *a higher industrial land share negatively correlates with fertility rates.* Finally, through the real-world application of the spacial-OLG framework to 2010 data, We find that the variations in the fertility rate across cities become more pronounced after the the elimination of the One Child Policy, suggesting that the impacts of land allocation and housing prices would magnify in the future.

My counterfactual policy analysis yields several additional insights. Notably, it is not surprising to find that fertility rates could potentially increase when land market or population control policies are relaxed. Quantitively, my estimation shows that 50.5% $((1.03-0.52)/1.01)$ of the fertility rate in China can be explained by the restriction of population control, while 7.92%$((0.6-0.52)/1.01)$ of the fertility rate can be attributed to the land misallocation over the past decades. Notably, under the One Child Policy, the observed fertility rate in the benchmark scenario is 0.52, which is significantly below the natural fertility rate needed for population stability (replacement level, 1.01). Even though, shifting to a free land market could potentially help China address the fertility rate gap by 16.33%, and increase the real income of residents by 5.43%. Keep all other conditions the same, if the government lift the One Child Policy and also let market force decide the land allocation, the aggregate fertility rate in China could increase from 0.52 to 1.02.

However, the increase in fertility rates following the relaxation of population or land policies predominantly results from the rise in births of "Lower-Education Children;" that is, parents tend to invest less in children's education when they decide to have more children. Intuitively, policy relaxations here reduce living and childrearing costs without affecting the expected marginal premium of education, resulting in a relative preference for lower education. To encourage long-run human capital accumulation, local governments could enhance the public education service and mitigate parents' financial burden of childrearing. For example, in my counterfactual analysis, double the efficiency of local public education service under the realized land scheme could increase the long-run skill ratio by 6.67%.

Literature This research closely links to four strands of literature. The first is to evaluate the impacts of land misallocation, where distortion is usually measured as a wedge between prices, as in Hsieh and Klenow (2009); Gyourko and Molloy (2015*a*). Concerning land policy, prior research, such as that by Gyourko and Molloy (2015*a*), indicates that stringent land-use policies push up housing prices, which reduces resident welfare and, at the macro level, impedes the efficient reallocation of labor across regions by restricting the movement of workers to more productive cities (Hsieh and Klenow, 2009). My work expands upon this body of literature by integrating dynamic population growth and demographic transitions into a spatial model, specifically accounting for variations in fertility rates and educational distributions.

Secondly, this paper contributes to the empirical literature on land market distortions in China, building on previous work by Tian, Zhang and Gong (2019), Fei (2020), and Tian, Wang and Zhang (2020). These studies provide extensive evidence that Chinese local governments offer industrial discounts to attract large firms with significant tax revenue potential, or industries with notable spillover effects. Lin and Zheng (2024) explain this phenomenon by calculating the Nash equilibrium and cooperative land allocation strategies when local governments are bidding for firms and labor across regions. In this paper, We identify consistent empirical patterns in industrial land discounts and treat them as a source of the rapidly increasing housing prices in China. We contribute to this literature by developing a unified framework that investigates the interplay between governments' land and population policy, thereby explaining multiple empirical patterns observed in China.

Thirdly, my paper builds upon the work of the family economy to examine the effects of macro policy on demographic features (Baird, Friedman and Schady, 2009; Becker, 1960). Various studies have demonstrated that housing wealth has a positive income effect on fertility rates in developed economies like the United States (Lovenheim and Mumford, 2010), Canada (Clark and Ferrer, 2016), and Denmark (Daysal et al., 2021). However, when it comes to developing countries like China, the empirical evidence regarding the influence of housing wealth on fertility rates has yielded different results. For instance, Liu, Liu and Wang (2023) found that higher housing prices significantly reduce the fertility probability among renter families and those with self-built homes, while the response was non-significant for homeowners. Additionally, Liu, Xing and Zhang (2020) discovered that among home-owning women, a 100,000-yuan increase in housing wealth led to a 14% decrease in the likelihood of giving birth. However, a recent study by Tan et al. (2023) found that housing wealth increased the likelihood of fertility by a significant margin of 3.6%. One possible reason for the perplexing outcomes is the strict One-Child Policy in China, which heavily contaminates the household's realized fertility choices. While there were variations in the implementation of this policy across different regions and for certain ethnic groups (García, 2022), the vast majority of individuals in urban areas were constrained by this policy until 2016. In this paper, We formalize the discontinuous price of the One-Child Policy and explore the effects of population policies under counterfactual scenarios.

Moreover, this project contributes to the literature evaluating the "Quantity-Quality" trade-off in fertility decisions within a spatial framework (Delventhal, Fernández-Villaverde and Guner, 2021; Greenwood and Seshadri, 2002). Most research on the declining fertility rate in developing countries overlooks this trade-off, resulting in less persuasive arguments regarding the welfare implications of long-term human capital accumulation. This study focuses on the "Quantity-Quality" trade-off in childbearing, which resonates with the One-Child Policy's objective of promoting "fewer and better births". We aim to assess the outcomes of this population policy and its interaction with public education policy.

Layout In Section II, We introduce the institutional background of China's land and population policies, and the datasets We employed. Section III analyzes land transaction records from the past decade and identify three stylized facts. We illuminate the issue of urban land misallocation in China, and construct a negative relationship between industrail land allocation and fertility rate. Building on these empirical insights, in Section IV, We develop a spatial-OLG model to capture the interplay of governments' land allocation, population controls, and public education expenditures on household family-planning decisions and migration dynamics. Section V defines the steady state in this model and explores the theoretical performance of households by a numerical simulation. In Section VI, We apply this model to real-world data and estimate model parameters. Section VII compares demographic outcomes across time and space under various counterfactual scenarios, and Section VIII concludes.

II. Institutional Background and Data

A. Land Allocation Policy

In 1988, the "Law of the People's Republic of China on Land Administration" authorized city governments to seize agricultural land from collectives and farmers, and convert it into construction land for sale to firms. [5]The cost of this conversion consists of two main components: compensation for the previous land users (typically rural collectives and farmers), and the cost of preparing the land for construction and installing necessary infrastructure such as roads, green spaces, water, electricity, and natural gas.

Urban Land Expansion and Quota Restriction Local governments in China have significant discretion over land supply, determining allocations for industrial and residential land. In 2004, the revised "Law of the People's Republic of China on Land Administration" introduced an approval process for land use: first, the central government formulates an overall plan for land use, controls the

[5]Construction land contains a variety of uses, including urban and rural residential and public facilities, industrial land, transportation and water conservancy facilities, tourism land, and military facilities.

total amount of construction land at the province level, and provides special protection for agricultural land.[6] Subsequently, provinces, cities, and counties then create their land usage plans accordingly and seek approval from their upper-level governments. These plans set targets for the total amount of construction land available (including both industrial and residential land). Once prepared, local governments can transfer land use rights through various ways, including one-to-one negotiation, bidding, auction, and listing. Over recent decades, there has been considerable growth in urban land areas as local governments have actively converted rural lands on city outskirts into urban districts, thereby expanding urban boundaries (see Figure A1).

Urban Land Usage Allocation In this paper, We concentrate on the two most crucial types of land usage: residential and industrial. Residential land is primarily utilized for real estate, especially multifamily apartments, while industrial land is used for factories and industrial parks. There are two reasons why we focus on these two types. First, these two categories constitute the major uses of urban land in China and display considerable variations in their distribution ratios across cities, as shown in Figure A2. Second, unlike land designated for roads, transportation, and public utilities, which typically take a steady share of urban space, industrial outputs are less bound to local constraints. This allows for industries to be concentrated in specific areas while serving global markets, giving local governments motivation to strategically prioritize industrial land. In this paper, We will use the areas of residential and industrial land to define the total land endowment and calculate their area ratio to define the land allocation.

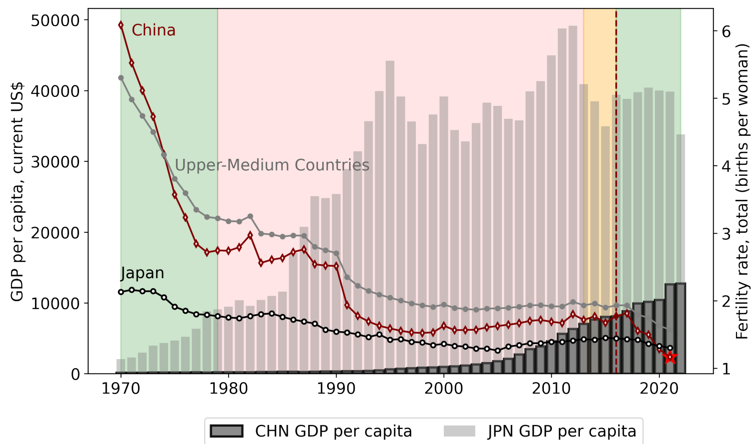
To investigate urban land allocation in China, We employ two datasets. The first dataset, "China Urban Construction Statistical Yearbooks" from the Ministry of Housing and Urban-Rural Development of China, represents the annual "STOCK" of urban land and helps illustrate the aggregate land allocation patterns and quantify the model. The second dataset, used in the empirical analysis section, consists of web-scraped data on urban land transactions over the past decade and represents the "FLOW" of urban land. This dataset records the unit price of each land parcel and is critical to identifying the urban land misallocation in the empirical section. Details about the regulations in land expansion and allocation are put in Appendix I.

B. *Population Policy*

Common wisdom attributes the declining population growth to the unique and strict One Child Policy (OCP) from 1979. The One-Child Policy in China was a population control policy that was introduced by the Chinese government in 1979 and lasted until 2015. The policy was implemented in response to concerns about the rapidly growing population in China and the strain this was putting

[6]For reference to the document, please see http://www.gov.cn/zxft/ft149/content_1144625.htm

Figure 2. Fertility Rate v.s GDP per capita: 1970-2022



Notes: Data Source: The World Bank: Fertility rate, total (birth per women). See https://data.worldbank.org/indicator/SP.DYN.TFRT.IN

on the country's resources (e.g, land) and economy. Under this policy, couples were only free to have one child, and had to pay heavy penalties for the second or third children, such as fines, loss of employment, and even forced abortions or sterilization (García, 2022; Ebenstein, 2010). The policy was strictly enforced, with several exceptions for ethnic minorities, scarcity of males in families, disabled first children, or types of jobs.[7] There is a general consensus about its unintended consequences, for example, a gender imbalance driven by a preference for male offspring, an increasingly aging population, and a looming shortage of workers needed to support the elderly.

However, academic debates continue regarding the causal relationship between this policy and the declining birth rate in China. For example, García (2022) argues that fertility rates in China and its surrounding countries were already decreasing even before 1979, and this decline persisted smoothly following the implementation of the policy. Various other elements, such as rising wages, improved educational levels, and agricultural reforms, might have also contributed to the continued reduction in fertility rates after 1979 (Huang, Lei and Sun, 2021). In this project, we model the implementation of the "One-Child policy" as a pricing system that increases the childbearing cost for women to have second and third children. This approach allows us to explore the potential human capital outcomes in a counterfactual scenario without this policy.

In 2015, the Chinese government announced that it would relax the One-Child Policy, allowing couples to have two children if either parent was an only child.

[7] According to government documents, there were seventeen individual characteristics qualified for "exemptions", see Scharping (2002) and García (2022) for details.

However, this has not led to a significant increase in the birth rate (Figure 1). Instead, China's birth rate kept falling. The Chinese government is now urging couples to have more children to address the country's demographic challenges: In 2015, China's fertility rate had dropped to 1.199 children per married woman, compared with 2.355 in the 1970s. This is below the replacement level of 2.1 children per married woman, which is needed to maintain a stable population. Besides, compared to a country with a reputation for its low fertility rate and aging structure, in 2020, with a per capita GDP that is only 26% of Japan's, China's birth rate started to be lower than Japan's (Figure 2).

III. Empirical Analysis

In this section, we display three stylized facts: First, industrial land is priced significantly lower than residential land. Second, this industrial discount varies across cities, with industrial regions exhibiting a larger price gap between land parcels. Third, an "oversupply" of industrial land, coupled with limited residential land, can drive up housing prices and living costs in cities, thus leading to a decline in fertility rates.

A. *Stylized Fact 1: Price Gap Between Industrial and Residential Land*

Figure 3 compares the average price of industrial land with commercial-residential land. Figure (a) aggregates the average price for all land sales from the year 2007 to 2019, while figure (b) uses the subsamples of land sales via public auctions. Both of them display a striking industrial discount. To further explore the price discount of industrial lands, we run regressions at the level of land parcels as follows:

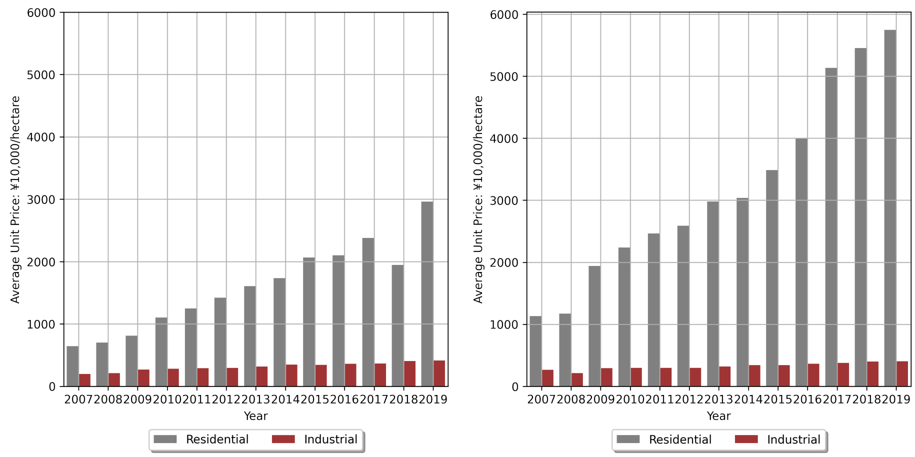
$$log(P_{ict}) = \beta_0 + \beta_1 IndD_{ict} + \beta_2 IndD_{ict} \times Dist_c + \beta_3 X_{ict} + \alpha_{ct} + \varepsilon_{ict} \quad (1)$$

Here, $log(P_{ict})$ is the unit price ($RMB10,000/ha.$) of the land parcel i in city c and year t, and $IndD_{ict}$ is a dummy variable shows whether the land is zoned for industrial usage. X_{ict} is a vector of parcel characteristics for each land sale, including the area of land, the rank of land quality [8], floor-area ratio (FAR) restrictions [9], the format of transactions(including government allocation, English auction, sealed-bid auction, and two-stage auction, with negotiation as a comparison), the source of land (new construction land, new construction land from the stock pool, and existing construction land), the distance to the city center, as well as the distance to the urban district center or rural county center. Specifically, we use the location of the government office building as the center of each city

[8] City governments categorize the urban land into different tiers based on the amenity quality of land, which is an indicator of the quality of the land.

[9] Floor-area ratio (FAR) refers to the building capacity per unit area of land, i.e. the ratio of building area to site area. Local government makes restrictions on both the upper and lower bounds of FAR when leasing the land.

FIGURE 3. UNIT PRICE OF INDUSTRIAL LAND AND COMMERCIAL & RESIDENTIAL LAND



(a) Price of all land parcels (b) Prices of land sold in auctions

Notes. The figures display the price gap between industrial land and residential land. Figure (a) uses the transaction information of all land parcels for the years 2007-2019, and figure (b) uses the subsamples of land sales via public auctions.

and county. All columns control for the fixed effect of city-year, and standard errors are clustered in the level of city-year.

In columns (2) of Table 1, we assume that residential developers would use up the floor-area ratio (FAR) of land, thus taking the unit price of residential lands over the upper bound of FAR and comparing it with the unit price of industrial land.[10] Column (3) takes into account the difference in official leasing time of these two lands: residential land at 70 years, and industrial land at 50 years. All of these regressions provide valid evidence for the industrial discount in the land market. Take the coefficient in column (2) in Table 1 as an example, industrial lands are leased at an average discount of 47% compared to that of residential land ($exp(-0.755) = 47\%$). More robustness checks are detailed in Appendix I.

[10]A potential concern of this regression is, that if land use differs between residential and industrial purposes, where residential use can build up and have a higher floor space on the same unit of land, people should be willing to pay more for the same plot of land. Then it would be reasonable for the price for a residential lot to be higher than a commercial lot of the same size. So the density of development, the ratio of floor space to ground area, matters. In reality, it is usually not the optimal design for most production processes to build up as tall as residential buildings due to indivisibility on the factory floor. In a few special cases, such as labor-intensive textiles, production could in principle take place in an "apartment" like setting where each worker sits on a table with a sewing machine, but that is likely a small fraction of industry nowadays. Therefore, we deal with the Floor-area ratio in column (2).

Table 1— Unit Price of Land on the Parcel Characteristics

VARIABLES	(1) $log(P_{ict})$	(2) $log(P_{ict}/floor)$	(3) $log(P_{ict}/time)$	(4) $log(P_{ict})$	(5) $log(P_{ict}/floor)$	(6) $log(P_{ict}/time)$
$IndDummy_{ict}$	-1.510***	-0.755***	-1.091***	-2.655***	-2.190***	-2.526***
	(-45.589)	(-26.714)	(-38.622)	(-10.255)	(-8.058)	(-9.296)
$IndDummy_{ict} \times Dist_c$				0.093***	0.117***	0.117***
				(4.449)	(5.460)	(5.460)
$log(dcity_{ict})$	-0.177***	-0.165***	-0.165***	-0.176***	-0.164***	-0.164***
	(-19.207)	(-22.664)	(-22.664)	(-18.804)	(-22.291)	(-22.291)
$log(area_{ict})$	0.007	0.023***	0.023***	0.006	0.021***	0.021***
	(1.266)	(3.748)	(3.748)	(0.946)	(3.353)	(3.353)
$[log(area_{ict})]^2$	-0.002	0.005*	0.005*	-0.003	0.004*	0.004*
	(-0.937)	(1.918)	(1.918)	(-1.300)	(1.662)	(1.662)
tansway_Allocation	-1.326***	-0.981***	-0.981***	-1.334***	-0.990***	-0.990***
	(-8.442)	(-6.558)	(-6.558)	(-8.471)	(-6.611)	(-6.611)
tansway_English	1.476***	1.616***	1.616***	1.493***	1.639***	1.639***
	(23.077)	(23.928)	(23.928)	(23.221)	(24.521)	(24.521)
tansway_Sealedbid	0.966***	1.193***	1.193***	0.958***	1.189***	1.189***
	(8.757)	(12.096)	(12.096)	(8.561)	(11.911)	(11.911)
tansway_Twostage	1.032***	1.211***	1.211***	1.034***	1.216***	1.216***
	(17.345)	(20.016)	(20.016)	(17.299)	(20.113)	(20.113)
FAR_lowbound	0.052***			0.052***		
	(3.836)			(3.842)		
FAR_upbound	0.144***			0.149***		
	(11.229)			(11.350)		
source_newD	-0.148***	-0.225***	-0.225***	-0.152***	-0.233***	-0.233***
	(-7.797)	(-7.058)	(-7.058)	(-8.020)	(-7.336)	(-7.336)
source_newstockD	-0.339***	-0.612***	-0.612***	-0.341***	-0.614***	-0.614***
	(-7.061)	(-7.489)	(-7.489)	(-7.113)	(-7.520)	(-7.520)
landrank	-0.029***	-0.034***	-0.034***	-0.029***	-0.034***	-0.034***
	(-7.274)	(-8.235)	(-8.235)	(-7.422)	(-8.435)	(-8.435)
City-Year FE	Y	Y	Y	Y	Y	Y
Observations	206,788	287,101	287,101	206,788	287,101	287,101
R-squared	0.661	0.618	0.620	0.662	0.619	0.621

Notes. This table displays the price gap between industrial land and commercial-residential land, controlling the information of each land parcel. Transaction records from 2007 to 2019 are used. Column (5) takes the unit price of residential lands over the upper bound of FAR and compares it with the unit price of industrial land. Column (6) further takes the unit price of industrial lands over the lower bound of FAR.

B. Stylized Fact 2: Price Gap is Wider in More Developed Region

To explore the spatial distribution of the price gap, in this reduced-form part, We use the city's distance to the nearest port $Dist_c$ as a proxy for the productivity level of a city and interact it with the industrial dummy in specification 1. A natural reason is, that after joining WTO in 2000, China's rapid growth was mainly driven by the reduction of external costs, and the effects of globalization are uneven among regions due to their proximity to the coast. For example, the comparative-advantage industries tend to locate closer to international gates, and large-scale workers move toward fast-growing coastal regions (Cosar and Fajgelbaum, 2016; WorldBank, 2009). Therefore, the distribution of local productivity is highly correlated with the spatial advantage to engage in trade liberalization.

Columns (4)-(6) in table 1 report the interactive effects of the industrial dummy along with the city's distance to the nearest port. The coefficients of interaction terms are positive and highly significant in all specifications, which means that moving the city inland leads to a smaller price gap. The prediction is, that keeping everything else equal, cities with higher productivity attract more firms to locate, thus leaving local governments higher-motivated to supply more industrial lands. To give a sense of the economic importance of the results, We use the interaction coefficient equal to 0.117 in column (5) as an example. Moving inland by 463 km, which is the median distance from the ports across prefectures, the unit price of industrial land per floor would increase for 136% ($exp(0.117 * log(463)) = 1.36$).

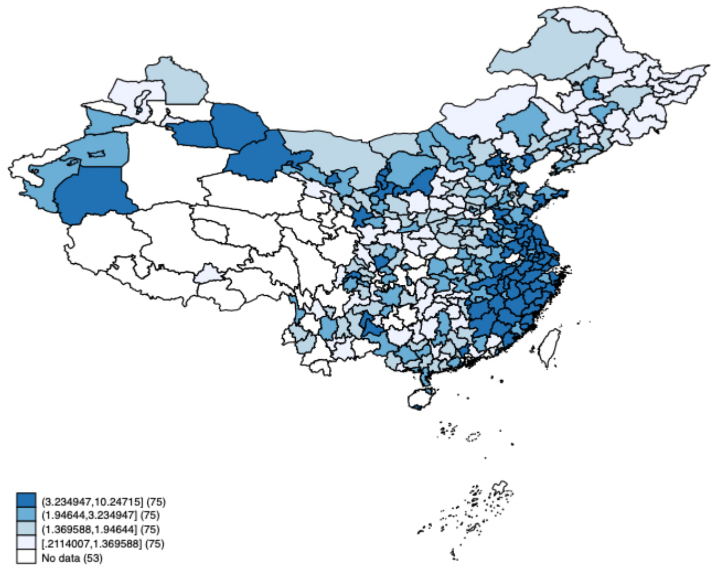
Figure 4 demonstrates the spatial distribution of the price gap across cities in China. We run regressions in column (2) according to Equation 1 for each city, and display the exponential of the coefficient of industrial dummy ratio $= 1/e^{\beta_1}$ in the map. Firstly, the eastern regions display a larger discount in the industrial land price, which fades out along the inner land. Secondly, the price ratio of residential-commercial land over industrial land ranges from 0.211 to 10.247, with the top quarter ranging from 3.25 to 8.04 (drop the highest 1%). The lowest quarter ranges from 0.26 to 1.37 (drop the lowest 1%), mainly lying in the northeastern area of China, which is regarded as a less-developed region for economic development.

C. Stylized Fact 3: Land Allocation and Fertility Rate across Cities

We first provide an overview of the relationship between land allocations, housing prices, and the aggregated fertility rate. The information on the Fertility Rate comes from the 2010 China National Census, which is calculated by the average number of live births in 2010 among married women aged 15-49 residing in urban areas at the prefecture level. The information on housing prices is sourced from the Economic Statistics Yearbook in 2010. We filtered and retained the sample of urban areas for analysis.

Figure 5 -(b) presents a scatter plot with a linear fit line, illustrating the negative relationship between the housing price-to-wage ratio and the married female

Figure 4. Geographical Distribution of Price Gap in China



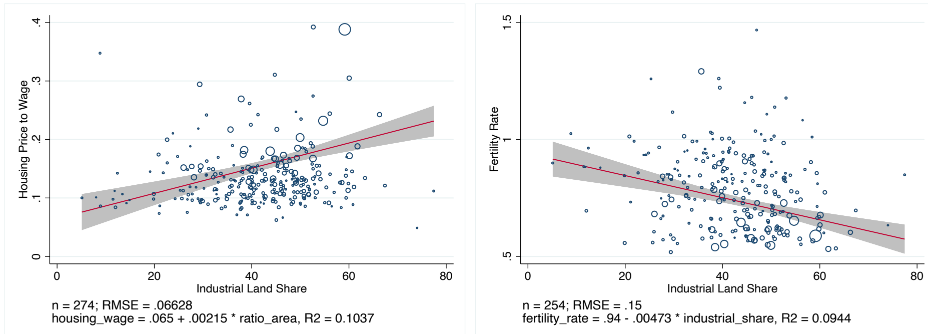
Notes. This map demonstrates the spatial distribution of the industrial discount of land prices across cities in China. We run regressions according to Equation 1 for each city and display the inverse exponential of the coefficient of industrial dummy $1/e^{\beta_1}$ in the map.

fertility rate across 285 prefecture-level cities in China (2010). The "Housing Price to Wage" ratio, calculated as house prices divided by the average wages of employed workers at the prefecture level serves as a measure of homeownership affordability for the working population in each city. In fact, the homeownership burden is most prominent in several big cities of China: According to Li, Qin and Wu (2020), the housing mortgage payment to income ratio has surpassed one in three superstar cities (Beijing, Shanghai, and Guangzhou), and has reached around 0.5 in second-tier cities in 2015, while the same ratio for others like New York and London is only around 0.3.

We then take a step backward and think about the causes of rapidly escalating housing prices. Many previous studies attributed the rapid housing price growth in China to the limited supply of *total* urban land imposed by the central governments (Fang and Huang, 2022; Deng et al., 2020) and the revenue-maximizing behavior of local governments in *allocating* the land usage (Henderson et al., 2022; He et al., 2022). Indeed, strict land use policies are found to push up housing prices in the U.S (Gyourko and Molloy, 2015*b*) and hinder the efficient allocation of labor across regions (Hsieh and Moretti, 2019). Figure 5-(a) demonstrates a positive correlation between higher housing prices and higher industrial-over-residential area ratios.

Due to the stringent enforcement of the One-Child Policy, all potential fertility

FIGURE 5. FERTILITY RATE, HOUSING PRICE AND LAND ALLOCATION IN CHINA, 2010



(a) (b)

Notes: The information on the Fertility Rate comes from the 2010 China National Census, which measures the average number of live births among married women aged 15-49 residing in urban areas at the prefecture level. Urban housing prices and wages are sourced from the Economic Statistics Yearbook in 2010, and "Housing Price to Wage" is calculated by the house prices over average wages of employed workers at the prefecture level and is utilized to assess the affordability of homeownership for the working population in a particular city. Urban industrial land shares are sourced from the Urban-Rural Construction Statistical Yearbook (2010).

willingness during this period would be constrained. One possible concern is that the variation in fertility rates across cities was primarily driven by the differentiated implementation of the One-Child Policy, which might make the relationship depicted in Figure 5 less convincing. To address this concern, we construct a variable to capture the implementation of the One-Child Policy at the city level, measured as the average permit price for having a second or third child.[11] All empirical results are detailed in the Appendix III. In summary, the empirical analysis indicates that over-supply of industrial land and so higher housing price could negatively affect fertility rates, even after controlling the variations in "One-Child Policy" implementation.

IV. Model

We now develop a spatial model that combines the population "Quantity-Quality" decisions, education investment, and migration choices. Time is discrete, and there are N locations in the economy. Individuals live for two periods: childhood and adulthood. There are two skill types of individuals: we denote those with a high-school degree as skilled s and those without as unskilled u. In the first period, children are born at their parents' places, receive their skill type chosen by their parents, and decide to migrate or stay at the end of that period. In the second period, after choosing the location, adults decide the time division

[11]We thank García (2022) for providing the datasets and codes for this measurement. However, all errors are my own.

between work and family, receiving wage payments and spending it on consumption goods and housing. Local governments in each city allocate the land, receive the rent revenue, and spend it on public education, which could reduce parents' financial burden on children's education.

In this draft, we only focus on urban areas, excluding rural areas, rural-urban migration flows, and the dynamic urbanization process in China during this period. The primary reason is that my dataset of land transactions only covers urban regions of China. One potential concern is that the fertility rate in rural areas is higher than in urban regions, and the migration flows from rural to urban areas are positive. Ignoring rural regions might lead to an overestimation of the fertility rate in urban areas. Here are two responses to address this concern. First, assuming that large-scale rural-urban migration flows are proportional to within-urban migration flows, then the cross-sectional population distribution in this model would remain unchanged.[12] Second, a worthwhile mental experiment is to add an aggregate rural area to the framework, creating an "N+1" location model. By assigning an exogenous fertility rate and outward net migration flow from this rural area, it would be clear that the population growth rate in the steady state should be lower in urban areas, compared to the current "N" urban location setting. Even though, while the estimation of urban population growth in my model might be overestimated, the population distribution across cities would not change. Due to the limited information on rural land areas, we will not extend this framework to include rural areas.

The distinction between skilled and unskilled labor in my study is based on educational attainment, with high school graduation serving as the threshold for two key reasons. First, the research aims to analyze educational investments from individuals' origin cities, but the available education data is based on their destination, working, or studying cities. Since college decisions in China are often made at a national level, this dataset may introduce a selection bias: cities with higher welfare, better education, or better job opportunities may attract individuals with higher education levels. In contrast, high school enrollment tends to be more localized, with students generally attending schools in their parents' cities. As Lu, Sun and Wu (2023) notes, 79% of high school students attended local high schools (non-migratants) in 2004. Secondly, the rate of college enrollment in China is relatively low. High school education in China is neither mandatory nor free of charge. In Table A1 of Appendix VI, we calculated the share of high shool education for each cohort from 4 million personal records from the 2010 National Population Census.[13] It shows that from 1980 to 2010, only 33.43% of

[12]This assumption would be more reasonable later given that the migration cost in my model is only destination-specific.

[13]In my definition, a cohort includes all individuals born within a one-year span, from September to August. Cohorts are identified by the year in which the majority of the members turn 15 and decide whether to attend high school. For instance, the 2008 cohort consists of individuals who turn 15 in 2008. In China, the official enrollment age for primary school is six years old, and primary school lasts six years, followed by three years of middle school. Consequently, most individuals decide whether to enroll in high school at the age of 15, though some may make this decision earlier or later. We constructed a

15-year-olds were enrolled in high school. Given these statistics, designating high school graduation as the benchmark for higher education is more suitable for my study.

A. Production

In period t, there is a given technology in each location to produce numeraire goods that are freely traded across regions. Specifically, in location j, the production function takes the following form:

$$Y_{jt} = K_{jt}^{1-\alpha} N_{jt}^{\alpha}$$

where Y_{jt} is output, K_{jt} is the industrial land input, and N_{jt} is the total efficiency labor units. N_{jt} takes the following form:

$$N_{jt} = \sum_{e=u,s} a_{ejt} \tilde{L} ejt$$

where $e = u, s$ denote two skill types (unskilled and skilled). a_{ejt} denotes the productivity of the certain type of individual, and $\tilde{L}_{ejt}$ is the working time of each type of labor. Given the local competitive factor market, we will have

$$p_{jt}^k = (1-\alpha)\left(\frac{N_{jt}}{K_{jt}}\right)^{\alpha} \tag{2}$$

$$w_{jt} = \alpha \left(\frac{K_{jt}}{N_{jt}}\right)^{1-\alpha} \tag{3}$$

$$w_{ejt} = a_{ejt} w_{jt} \tag{4}$$

where p_{jt}^k is the rent for local industrial land, and w_{ejt} is the labor income to local individuals with specific education.

B. Adult's Decision Making

Adult's decision-making is the main component of the model. For an individual o in location j with skill type e at period t, her preference is given by:

$$U(c_t, h_t, n_t, e') = B_{ejt}\{\underbrace{[(1-\gamma)log(c_t^y) + \gamma log(h_t^y)]}_{\text{Consumption Utility}} + \underbrace{\chi[log(n_t) + \mathbb{E}[O_{e'jt}] + \varepsilon_{ejt}]\}}_{\text{Childbearing Utility}}$$

dataset for city-cohorts from 1980 to 2008, defining a city's high school education rate as the ratio of individuals who received at least a high school education to the total population in the same cohort.

where c denotes consumption of numeraire good, h denotes consumption of residential land, n and e' denotes the number and education type of children. The first line is the simple Cobb-Douglas preference on numeraire goods and housing, while the second line denotes the utility obtained from childbearing. Specifically, parents derive utility from both the number (n_t) and the expected utility of their children ($\mathbb{E}[O_{e'jt}]$), taking a forward-looking expectation over the children's welfare in the next period. $O_{e'jt}$, the realized utility of their children in the next period, is both specific for workers' skill types and location chocies. ε_{ejt} is the idiosyncratic preference shock for education and location preference realized before making decisions, that is, $\varepsilon_{ejt} = \varepsilon_{jt} \times \varepsilon_{et}$. Intuitively, given different preferences over children's education (ε_{jt}), and locations (ε_{et}), the same type of individuals make different decisions on the number and education of childbearing. We assume that all the children in one family will receive the same education. B_{ejt} denotes the amenity of a city that, while not influencing parent's childbearing decisions, impacts children's migration choices in the last period. The budget constraint is as follows:

$$c_t + p^h_{jt}(h_t + \tau^h_t n_t) = w_{ejt}[1 - n_t(\tau^w_t + \tau^e_{ee't} + f * \mathbb{1}\{n > \overline{n}\})] \tag{5}$$

Bearing n_t children is associated with four following costs: firstly, a fixed proportion τ^w_t of unit working time to raise a child; secondly, another proportion $\tau^e_{ee't}$ of unit working time to educate children to type e'; thirdly, parents also need to purchase an extra housing space τ^h_t for each newborn; finally, a penalty, f, if breaking the One Child Policy (OCP), applicable when the number of children is greater than the legal quota: $\mathbb{1}\{n > \overline{n}\} = 1$. According to Ebenstein (2010) and Yin (2023), during the implementation of "One-Child Policy", provinces could be grouped into three categories: 1-child zones, 1.5-child zones, and 2-child zones. In the 1-child (or 2-child) zones, each couple was limited to having at most 1 (or 2) children. In the 1.5-child zones, rural couples were allowed to have a second child if the first was a daughter, so the quota was 1.5 for rural couples and 1 for urban couples. They then weighted the child quota at the province level with employment in 1982 to get the child quota at the national level. This weighted average is 1.7794 for rural couples and 1.0374 for urban couples. Since there is only one parent in a household in my model, we divide the numbers by 2 and get $\overline{n} = 0.5187$ for urban areas.

Suppose that now the parents are determined to give their education type e', then we can solve the decision-making problem for adults as follows:

$$c_{ejt} = \frac{1-\gamma}{1+\chi} w_{ejt}; \tag{6}$$

$$h_{ejt} = \frac{\gamma}{1+\chi} \frac{w_{ejt}}{p^h_{jt}} \tag{7}$$

$$n_{ee'jt} = \frac{\chi}{1+\chi} \frac{w_{ejt}}{(\tau^w_t + \tau^e_{ee't} + f_{jt} * \mathbb{1}\{n > \overline{n}\}) w_{ejt} + \tau^h_t p^h_{jt}} \tag{8}$$

Note that the first two variables do not depend on children's education type. The number of children is positively influenced by the parent's preference for children χ and their income w_{ejt}. It is also negatively correlated with the childbearing cost τ^w_t and $\tau^e_{ee't}$, and the housing price could restrict the fertility rate as each child would take up an inelastic housing space τ^h_t. Given these decisions, we can also derive the indirect utility function for adults:

$$\begin{aligned} V^o_{ejt} &= (1+\chi) log(w_{ejt}) - \gamma log(p^h_{jt}) \\ &+ \chi \left\{ \mathbb{E}[O_{e'jt}] - log[(\tau^w_t + \tau^e_{ee't} + f_{jt} * \mathbb{1}\{n > \overline{n}\}) w_{ejt} + \tau^h_t p^h_{jt}] \right\} + \epsilon^o_{ejt} \end{aligned}$$

Note that only the component in the second line is contingent on the choice of children's education type, e'. We assume that ϵ^o_{ejt} is i.i.d. for all adults drawn from a Gumbel distribution with scale parameter $\frac{\sigma_E}{\chi}$. The shock is realized at the beginning of the period. Adults observe the realization and determine the children's education type that brings them higher utility. As a result, the education transition ratio $\pi^E_{ee'jt}$ will be:

$$\begin{aligned} \pi^E_{ee'jt} &= Prob(\text{parents of type e giving children education type } e') \\ &= \frac{\text{number of type e adults giving children education type } e'}{\text{number of type e adults}} \\ &= \frac{\left[\frac{exp\{\mathbb{E}[O_{e'jt}]\}}{(\tau^w_t + \tau^e_{ee't} + f_{jt} * \mathbb{1}\{n > \overline{n}\}) w_{ejt} + \tau^h_t p^h_{jt}} \right]^{1/\sigma_E}}{\sum_{e'=u,s} \left[\frac{exp\{\mathbb{E}[O_{e'jt}]\}}{(\tau^w_t + \tau^e_{ee't} + f_{jt} * \mathbb{1}\{n > \overline{n}\}) w_{ejt} + \tau^h_t p^h_{jt}} \right]^{1/\sigma_E}} \end{aligned} \tag{9}$$

Intuitively, the educational investment share depends on the trade-off between the payoff of children's education type in $\mathbb{E}[O_{e'jt}]$ (skill premium) and four childbearing costs of each type. Given this distribution, we can now write down the total efficient labor supplied to firms:

$$\begin{aligned} N_{jt} = a_{ujt}L_{ujt}[1 - \sum_{e'=u,s} n_{ue'jt}\pi^{E}_{ue'jt}(\tau^{w}_{t} + \tau^{e}_{ee't})] \\ + a_{sjt}L_{sjt}[1 - \sum_{e'=u,s} n_{se'jt}\pi^{E}_{se'jt}(\tau^{w}_{t} + \tau^{e}_{ee't})] \end{aligned} \tag{10}$$

Here, we subtract a portion of time from workers' efficient production to capture the opportunity cost of childbearing. These adjusted labor units would be used to clear the labor market and pin down the wage.

C. Migration

In the model, children barely make any decision, except at the end of the period they decide where to live for their adulthood. Similarly, we impose an idiosyncratic extreme value distributed preference shock to each location. Then we have the following migration matrix:

$$\begin{aligned} \pi^{M}_{eijt} &= Prob(\text{share of type e born in city i migrates to city j}) \\ &= \frac{\text{number of type e living in city j}}{\text{total number of type e across the country}} \\ &= \frac{\mathbb{E}[B_{ej,t+1} exp\,\{V_{ej,t+1}\}]^{1/\epsilon_M}}{\sum_{k=1}^{N}\mathbb{E}[B_{ek,t+1} exp\,\{V_{ek,t+1}\}]^{1/\epsilon_M}} \end{aligned} \tag{11}$$

There are two things worth noting: firstly, with this representation, we implicitly assume no migration cost; secondly, we augment the utility with quality-of-life amenities in each location, which will be calibrated to accommodate population distribution later on. Based on this migration pattern, from the perspective of parents, the expected utility for children before the drawing of their location preference shock is (see details of derivation in Appendix IV).

$$\mathbb{E}[O_{ejt}] = \sigma_M \log\left(\sum_{k=1}^{N}\mathbb{E}[B_{ek,t+1}V_{ej,t+1}]^{1/\sigma_M}\right) \tag{12}$$

D. Land Allocation and Other Conditions

Land Market Clearings We assume that in each location there is an exogenous total land endowment (or quota restricted from the upper governments), $\bar{X}_{jt}$, and local governments allocate a proportion into industrial use k_{jt}, such that:

$$K_{jt} = k_{jt}\bar{X}_{jt}; \quad H_{jt} = (1 - k_{jt})\bar{X}_{jt} \tag{13}$$

Both the industrial and residential land markets will be cleared at each location, such that:

$$(1-\alpha)Y_{jt} = p^k_{jt}K_{jt} \tag{14}$$

$$p^h_{jt}H_{jt} = \frac{\gamma}{1+\chi}\sum_{e=u,s} w_{ejt}N_{ejt} + p^h_{jt}\tau^h_t \sum_{e=u,s}\sum_{e'=u,s} \pi_{ee'jt}n_{ee'jt}L_{ejt} \tag{15}$$

For Equation 14, it is intuitive that the total revenue in the industrial land market equals the firms' expenditure on industrial land. For Equation 15, the total revenue in the residential land market includes both the expenditure share that parents pay for enjoyable housing and the inelastic housing space they must pay for their children.

Public Education Expenditure We assume that local governments spend their land rent revenue on public education services, such that governments' simple budget constraints would be:

$$L^c_{ejt}E_{jt} = p^h_{jt}H_{jt} + p^k_{jt}K_{jt} \tag{16}$$

Here, E_{jt} denotes the unit expenditure that local governments spend on per student for public education services. we assume that this expenditure reduces parents' burden in educating children. Specifically, we assume that educating an unskilled child takes no cost for either type of parent, $\tau^e_{su',jt} = \tau^e_{us',jt} = 0$. However, unskilled parents have to pay more than skilled parents to raise a skilled child, and both incur a non-zero cost. The intercept term in Equation 17, τ_{e0}, represents this basic cost of children's education, and so $\tau^{e0}_{us',jt} > \tau^{e0}_{ss',jt} > 0$. The coefficient term, τ^{e1}, reflects the public education services provided by local governments, which are assumed to be the same for both types of parents.

$$\tau^e_{es,jt} = \tau^{e0} - \tau^{e1} log E_{jt} \tag{17}$$

This mechanism is supported by two key aspects of China's local public finance system. First, in 2002, Chinese central government started taking 50% of the income tax (both corporate and individual) from local governments, increasing this share to 60% in 2003. In contrast, all revenue from urban land sales belongs to the urban local governments, and revenue from rural land sales belongs to rural collectives. Figure A1 in Appendix VI illustrates that from 1999 to 2016, land sale revenues accounted for an average of 40.78% of total local fiscal revenues. During the sample period of 2007-2013, this proportion was even higher, reaching 53.43%. These revenues covered about 50% of physical infrastructure investments, inclduding transportation facilities and educational zones, while the remaining 50% financed by loans using land as collateral, as indicated by Ding (2003).

Second, according to the 2022 public education report, about 80% of the total national education funding comes from state financial education funds, making government investment the largest source of educational funding. Of these state financial education funds, 80% is sourced from the general public budget for education, making education the largest expenditure in the general public budget. Within the national general public budget for education, 80% comes from local sources, making local governments the primary entities responsible for educational expenditures.[14] As my model focuses on local education expenditure before college, it relies heavily on local public funding. Figure A2 in Appendix VI displays the distributions of local land revenue in China and its positive relationship between K-12 public spending per student in each city.

Equilibrium Take government policies as given, including land allocations $\{H_{jt}, K_{jt}\}$ and population policy with one-child fine f_{jt}. Given a sequence of locational fundamentals, $\{a_{ejt}, B_{ejt}\}$, a competitive equilibrium in any time t is a sequence of wages w^x_{ejt}, housing price p^h_{jt}, industrial land price p^k_{jt} and a sequence of household allocations $\{c_{jt}, h_{jt}, n_{ee't}\}$ such that firms maximize their profits, households maximize their utility, governments balance their budgets and both the labor and land markets clear.

Population Transition As each generation dies out after their second period, the newborns will grow up and migrate to form new population distributions in the next periods:

$$L^c_{e'jt} = \sum_{e=u,s} L_{ejt}\pi_{ee'jt}n_{ee'jt} \tag{18}$$

$$L_{ej,t+1} = \sum_{i=1}^{N} \pi^M_{eijt} L^c_{ejt} \tag{19}$$

Here, a realized population distribution in period $t+1$ is associated with a sequence of corresponding local welfare values, $\{V_{ej,t+1}\}$. To connect the equilibria across periods, the expectation of children's utility in the previous period, $\mathbb{E}[O_{e'jt}]$, should be rationalized according to Equation 12.

E. Benchmark: a Simplified Market Equilibrium

We consider a counterfactual equilibrium where land allocations are determined in each city by local landlords maximizing the total revenue from land sales. Assume that the land market is perfectly competitive in each city. Then, in this market equilibrium, the prices of two lands should be driven to be the same, $p^K = p^H$. In this case, let N denote the aggregate supply of efficient labor units

[14] https://www.gov.cn/xinwen/2022-09/28/content_5713042.htm

in one place at a time (subscripts neglected), then we have

$$\begin{aligned} p^K K &= (1-\alpha)Y \\ WN &= \alpha Y \\ p^H H &= \frac{\gamma}{1+\chi} WN + p^H \tau_h \pi^E nL \end{aligned}$$

The last term on the right side of the third equation is the part with no analytic solutions, as it involves childbearing decisions in this model. In the next section, we will simulate market outcomes by having each city repeatedly adjust its land allocation share until the price of industrial land equals that of residential land in each city. To provide an intuition about this "efficient" land allocation, let's reduce the values of the childbearing cost parameters, effectively ignoring their impact on the residential land market's clearing conditions and labor supply (disregarding the last term in the third equation). Combine these three equations and impose that $p^K = p^H$, we have

$$\frac{H}{K} = \frac{\alpha}{1-\alpha} \cdot \frac{\gamma}{1+\chi} \tag{20}$$

Intuitively, the efficient land allocation between two types of land depends on three parameters: the land intensity in the production function, $1-\alpha$; the housing share in household expenditure, γ; and the preference for childbearing, χ. Therefore, in this numerical approximation, the market equilibrium will feature the same land allocation across cities.

Local Utility Optimization Here we present a generalized framework to demonstrate that if governments are maximizing local utility of residents, an "optimal" land allocation should also lead to an equal price between residential and industrial land. Note that assume all land sales revenue will be rebated to local workers, then all industrial output product will be consumed by household, that is, $Y = C$. Consequently, the utility function of workers could be define as:

$$U = U\left(\frac{Y(K,L)}{L}, \frac{H}{L}\right)$$

where K and H denote the industrial land and residential land, respectively; and L is the workers in the economy. Under an optimal land allocation maximizing the household's utility, the marginal contribution of two lands to utility should be equalized, that is:

$$\frac{\partial U}{\partial H} = \frac{\partial U}{\partial Y}\frac{\partial Y}{\partial K}$$

Meanwhile, from the firm's optimization problem, the price of industrial land should equal its marginal product:

$$p^K = \frac{\partial Y}{\partial K}$$

and, from worker's optimization problem, the price of residential land and consumption goods would be determined by their marginal utility, respectively:

$$\begin{aligned} \lambda p^H &= \frac{\partial U}{\partial H} \\ \lambda p^c &= \frac{\partial U}{\partial C} = \frac{\partial U}{\partial Y} \equiv \lambda \\ \Rightarrow p^H &= \frac{\partial U / \partial H}{\partial U / \partial Y} \end{aligned}$$

where λ is the Lagrangian multiplier. Therefore, when the two prices are equal, we have:

$$\begin{aligned} \frac{\partial Y}{\partial K} &= \frac{\partial U / \partial H}{\partial U / \partial Y} \\ \Rightarrow \frac{\partial U}{\partial H} &= \frac{\partial Y}{\partial K}\frac{\partial U}{\partial Y} = \frac{\partial U}{\partial K} \end{aligned}$$

That is, when the two prices are equal, we exactly equalize the marginal contribution of residential land and industrial land to worker utility. However, during this process, if any portion of the land revenue is kept by landlords or local governments, it reduces the income available to workers, thereby lowering the price of residential land under the same allocation scheme (derived from the housing market clearing condition). Furthermore, from the illustration above, we can see that this price equalization rule holds not only for the specific Cobb-Douglas (CD) function initially assumed, but also for a more general form of production functions and worker preferences.

To sum up, a generalized spatial framework suggests that to maximize worker welfare, the price of residential land should be equal to or lower than that of industrial land. **This finding supports that the price gap (industrial land discount) we found in the empirical section indicates a misallocation of land.**

V. Comparative Static Analysis

In this section, we start with a numerical simulation of varied land allocation regimes to explore some comparative statics in a static equibrium of this economy. For now, we take all local fundamentals as given, including city productivity $A_{ejt} = 1$ and amenity $B_{ejt} = 1$. These parameters will be internally calibrated in the next section. Notably, this model is iterative, where parents consider the expected utility of their children in the next period ($\mathbb{E}[O_{ejt}]$ in Equation 12) when making family plans. In the comparative static analysis of this section, we temporarily assume that all parents have the same numerial expected utility and compare the family-planning outcomes in a static equilibrium. In the next section, we will calculate the expected future utility by solving for the steady state.[15]

A. *Parameterization*

We set some parameters to their data counterparts or borrow them from other studies as shown in Table 2. The land intensity of production, $1-\alpha$, is set to 0.08. Ákos Valentinyi and Herrendorf (2008) takes the land share of 0.05 for the industry in the United States and Henderson et al. (2022) increases it to 0.07 to capture the more land-intensive nature in China's industry between 2008 and 2015; we further increase this intensity to 0.08. Housing expenditure is calculated from the 2009 Urban Household Survey. We summed the annual spending on housing rent, utilities, service fees, purchase, building, loans, and funds, then calculated the average share of these expenses in a household's annual expenditure, resulting in $\gamma = 0.137$.

There are two childrearing costs to estimate in this model. The first component denotes the cost to raise a child, no matter what type of child they have. It contains three parts: the opportunity cost of working time, denoted as τ_t^w in Equation 5; the unit of housing space for each child τ_t^h; and the fine for an extra child if violate the one-child policy f. We adopt the opportunity cost from Yin (2023) but set $\tau^w = 0.15$. The housing space unit τ^h is a unique parameter in my model and we set it to be 0.1 for each child. We bring the weighted average fine rate of One-Child Policy in China between 1979 and 2000 from Ebenstein (2010) and Yin (2023), which is $f = 0.1594$ [16]. The second component, educational expenses for their children, denoted as $\tau_{ee'jt}^e$ in Equation 5, is specific to both parents and children. We first assume that the education costs for a lower-educated child are zero, regardless of whether the parents are

[15] A steady state is required because fertility decisions involve a rational expectation of the utility of the next generation, which is easiest to deduce in a steady state. However, in the steady state, the average fertility rate across the country would be one (definitions and details are provided in the next section), which make the comparision of fertility rate across steady states trivial. In addition, it implies that, beyond the direct effect of local fundamentals on fertility, there is also an indirect effect coming from different population scales in steady states. To eliminate the indirect effects, we will fix a constant numerical expected utility in the comparative static analysis in this section, and then derive and compare the transitional paths in the next section.

[16] As noted by Yin (2023), fines are proportional to parental income and vary across provinces and over time (Scharping, 2013). In this model, to convert monetary fines to time costs, consider this example: In Shanxi Province in 2000, a couple would incur a fine equivalent to 1.29 times their annual income for a second child. Given that my model accounts for only one parent per household, the fine equates to $1.29 \times 2 = 2.58$ times the annual income of a single parent. With an assumption of a 20-year working life, the equivalent time cost in this province is $2.58/20 = 0.129$. Data on provincial fines from 1979-2000, sourced from Ebenstein (2010), are averaged based on each province's employment share in 1982, resulting in a national average fine rate of 0.1594.

skilled or unskilled. Then, for a higher-educated child, the education cost is a function of public education expenditure, and it involves three parameters to calibrate in Equation 17: the intercept term for skilled ($\tau^{e0}_{ss'}$) and unskilled ($\tau^{e0}_{us'}$) parents, and we set them to be 0.03 and 0.01, respectively; and a coefficient term τ^{e1}, denoting the effects of public education, which is set at 0.05.

Table 2—Parameters Calibrated Externally

Parameters	Definition	Value	Source
α	Land intensity in production	0.08	Valentinyi (2008) and Henderson (2023)
γ	Expenditure share on housing	0.4407	National Bureau of Statistics (1990)
f	Fine with one child policy	0.1595	Yin (2023)
χ	Preference for childbearing	0.5	
τ^{w}_{jt}	Opportunity cost for childbearing	0.15	
τ^{h}_{jt}	Housing space per child	0.1	
$\{\tau^{e0}_{ss'}, \tau^{e0}_{us'}\}$	Intercept term	$\{0.03, 0.01\}$	
τ^{e1}	Coefficient term	0.05	

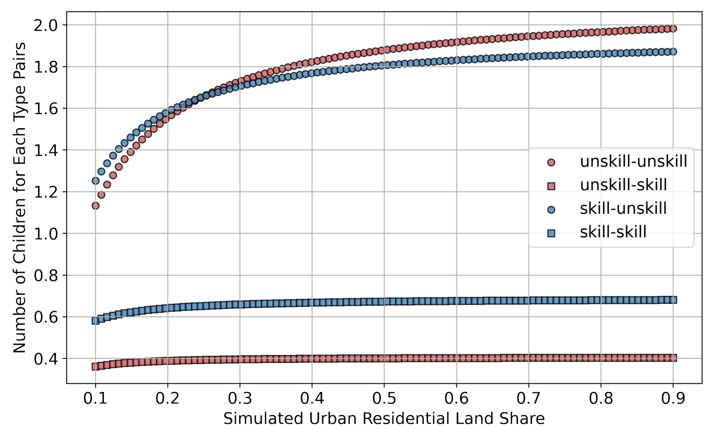
B. Numerical Comparative Statics

We first simulate the model using 100 cities with identical productivity and amenities ($A_i = A_j = 1; B_i = B_j = 1$), varying the housing land allocation share from 0.1 to 0.9. Figure 6 shows the number of children for each "Parent-Children" skill type pair, tageting an expected utility of chilren in the next period of $\mathbb{E}[O_{ejt}] = 10$, as the residential land share increases from 0.1 to 0.9. There are two key takeaways from this figure: First, increasing the share of residential land can significantly raise the fertility rate, particularly the number of unskilled children. Intuitively, increasing the housing land share primarily reduce living and childrearing costs, yet rarely affecting the expected marginal premium of education (skill premium of wage), resulting in a relative preference for lower education. Second, income effects play a dominant role in fertility decisions, as skilled parents can afford more children than unskilled parents. Figure 7 compares the aggregate fertility rate with and without the One-Child Policy fine. Here we sum up the total number of children differentiated by their education levels, born to parents of varying skill sets, and divide it by the overall population of parents to obtain the aggregate fertility rate in this economy:

$$f = (\sum_{e=u,s} L_e \sum_{e'=u,s} n_{ee'} \pi^{E}_{ee'}) / \sum_{e=u,s} L_e$$

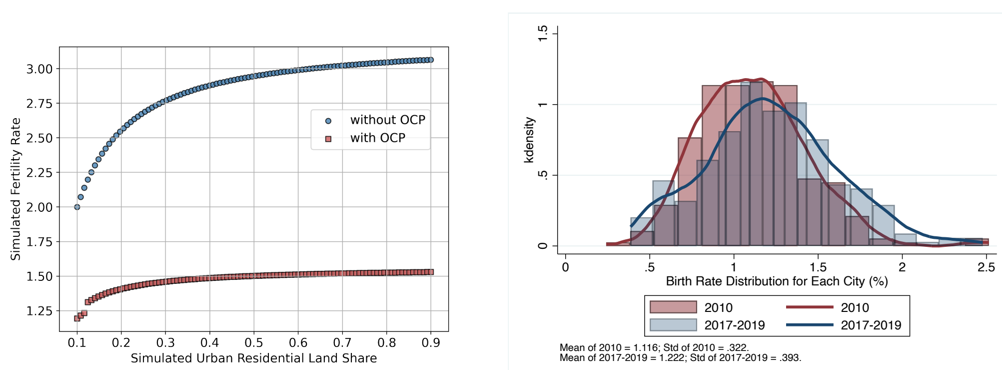
Two key takeaways from this figure: First, the aggregate fertility rate continues to increase with the residential land share and rises further when the One-Child Policy fine is removed. Second, variations across cities increase after the elimination of One-Child Policy fine, indicating that now the effect of land allocation and

FIGURE 6. FERTILITY RATE OF SKILL PAIRS IN THE STEADY STATE



housing prices is amplified. This pattern aligns with the empirical data in Figure 7-(b), which shows that in 2010, when the One-Child Policy was in effect, city birth rates were more concentrated and had a smaller standard deviation; however, in 2017-2019, following the relaxation of fertility restrictions, city variations increased, leading to a more dispersed distribution.

FIGURE 7. SIMULATED FERTILITY RATE



(a) Aggregate Fertility Rate

(b) From Data: Fertility Rate Distribution

We compare the simulated results with the real-world land allocation with a theoretical scenario with a free land market in each city. To achieve this, we begin by importing data on land allocations from 240 cities, sourced from the 2010 China Urban Construction Statistical Yearbook. Productivity and amenity values are still assumed to be uniform across all cities. Each city then reallocates its share of industrial land while maintaining the total land area from data, adjusting until the prices of both land types are equal within the city. We then calculate the equilibrium outcomes under this simulated land allocation, specifically the fertility rate and industrial outputs.

Figure 8 compared the residential land share between these two allocation regimes. In Figure (a), the blue markers represent the realized share of residential land area in each city (from the data), while the red markers are the simulated land share in the theoretical market equilibrium. We find that governments' real-world allocations tends to prioritize industrial land, leading to a reduced residential share. As derived in Equation 20, the efficient land allocation under a free land market mainly depends on three parameters and so is uniform across cities: the land intensity in the production function $1 - \alpha$; the housing share in household expenditure, γ; and the preference for childbearing, χ. In this simulation, we solve the entire model, incorporating the non-linear fertility decisions influenced by the One-Child Policy fines. Consequently, the simulated efficient land allocations exhibit slight variations across different cities.

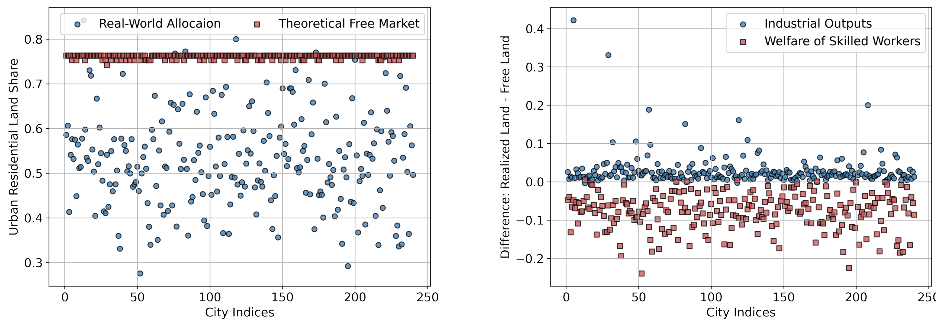
To further explore local governments' motivations, Figure 8-(b) compares the difference in industrial output and household welfare between these two land regimes. For each city, the difference in industrial output - calculated as the output under the realized land allocation minus that under a theoretical free land market - is represented by blue points. These points predominantly appear above the zero axis, indicating that land allocations by local governments tend to yield higher industrial outputs. Conversely, the differences in social welfare between these regimes are depicted in red and mostly fall below zero, suggesting that a free land market could potentially enhance social welfare (Unfortunately, local governments did not choose this option in reality.)

VI. Model Fitting and Calibration

In this section, we will apply the theoretical framework to match real-world data and estimate model parameters. First, this model is dynamic, where parents would take into account the expected children's future utility ($\mathbb{E}[O_{ejt}]$ in Equation 12) when making the family plans. To solve this iterative system, we begin by calculating this expected future utility through solving for the steady state. At the end of each period, children grow up and select their locations for adulthood, resulting in a new population distribution (and so the local welfare $V_{ej,t+1}$) for the next generation. Here, in my model, a "steady state" is defined as the condition where the newly realized population distribution across cities after children's relocation decisions remains the same as that from the previous period, and so do the utilities.

Then, we would delineate the transitional path toward a steady state, as shown in Figure 9. This path treats 2010 as a reference period, aligning it with real-world data, where both residential and industrial land areas are allocated by local

Figure 8. Compare with the "Efficient" Land Allocation



(a) Land Allocations

(b) Equilibrium Outputs

Notes: Figure (b) displays the difference in industrial output and household welfare between these two regimes. For each city, the difference in industrial output is calculated as the output under the realized land allocation minus that under a theoretical free land market, and represented by blue points. The differences in social welfare between these regimes are depicted in red.

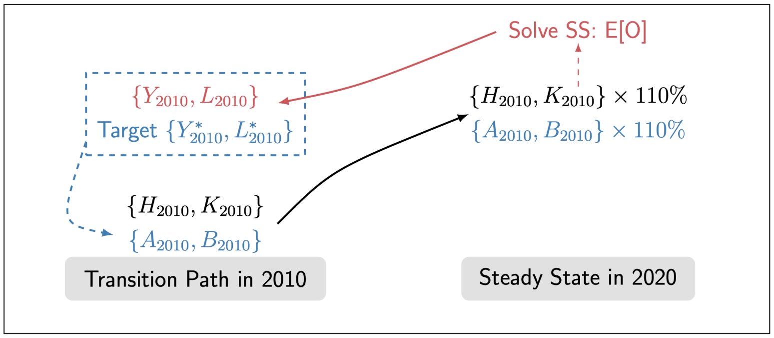
authorities, and households face a fine under the One Child Policy for having a second child. As the model progresses to 2020, several changes occur: the One Child Policy is abolished, productivity (denoted as A_{ejt}) increases (assumed 10% for ten years), and urban land undergoes expansion, leading to a new population distribution and economic equilibrium.

We treat the year 2010 as a point on the transitional path rather than as an initial steady state for a practical reason: in a steady state, the average fertility rate of a country would be zero under a One-Child Policy fine and one if the fine is canceled. Consequently, analyzing fertility rates in steady states under different counterfactual policies would lead to trivial results. Therefore, we choose to calibrate the transitional path as shown in Figure 9, with all counterfactual analysis in the next section focusing on the transitional period, year 2010.

A. *Steady State*

In Appendix V, we discuss the uniqueness of steady state by two steps. First, at the cross-sectional level, we provethe spatial equilibrium is unique. Specifically, given initial populations (L_{u1t}, L_{s1t}) and utilities (V_{u1t}, V_{s1t}) for location one, there exists only one corresponding population vector (L_{ujt}, L_{sjt}) for any other location j. Consequently, the aggregate national population is unique. Secondly, at the cross-time level, we prove that at the aggregate level, considering the nation as a whole, the solution to the steady-state condition-where the population in the next period remains the same as in the current period-is also unique.

FIGURE 9. FRAMEWORK FOR TRANSITION PATH



Notes: The black arrow represents the forward calculation, transition from the year 2010 to the steady state in 2020; the red arrow denotes the backward process from the model; the blue terms denote the calibration process to align with observed data.

Algorithms to Calculate the Steady State Based on the definition of steady state, the algorithm to calculate a steady state is as follows :

1) Initialize with a guess of $\{V_{uj}, V_{sj}\}$ and $\{L_{uj}, L_{sj}\}$
2) Calculate $\{O_{uj}, O_{sj}\}$ out of the guess based on Equation 12.
3) *Take* $\{O_{uj}, O_{sj}, L_{uj}, L_{sj}\}$ *as given, calculate all other equilibrium outcomes*
4) Update $\{V_{uj}, V_{sj}\}$ and $\{L_{uj}, L_{sj}\}$ from equilibrium outcomes
5) Iterate the procedures until convergence

As outlined in step 3), we will need to calculate the households' policy functions for each location based on the available population (L_{ejt}) and utility distribution (O_{ejt}), specifically focusing on fertility rate ($n_{ee'jt}$), education probability ($\pi^E_{ee'jt}$), and migration choices ($\pi^M_{ee'jt}$). These calculations are not trivial, as $n_{ee'jt}$ and $\pi_{ee'jt}$ show up in several equations including labor supply, education expenditure, and the clearing conditions of residential land market. Therefore, we approach their resolution with a systematic iterative method:

1) Initialization: Start with an initial guess for $n^0_{ee'jt}$ and $\pi^0_{ee'jt}$.
2) First Iteration:

   - Using the initial guesses, calculate the total labor supply (N_{jt}) according to Equation 10 and derive the corresponding wages by Equations 3 and 4.
   - Determine residential land prices from the market-clearing condition in Equation 15.

- Calculate per-capita education expenditure from Equation 16, which in turn affects the cost of childbearing via Equation 17.

3) Update: Incorporate the derived childbearing costs, wages, and land prices to update the childbearing and education decisions according to Equations 8 and 9, resulting in $n^1_{ee'jt}$ and $\pi^1_{ee'jt}$.

4) Convergence Check: Repeat the iterative process until the values for $n_{ee'jt}$ and $\pi_{ee'jt}$ converge.

B. Transition Path

The delineation of the transition path involves two calculations: forward and backward. First, assuming a swift transition to a new steady state in 2020, we calculate the expected utility for children in 2020. This expected utility is then used to back-out the fertility decisions one period ahead (red arrows in Figure 9). Simultaneously, the population scale and skill ratio are adjusted to adhere to the transition rules across periods, as shown in Equations 18 and 19, ensuring that the aggregate number of newborns in this period would be able to generate the future population distribution for the next period (black arrows in Figure 9). Additionally, as an outer loop, we iteratively adjust local productivity and amenities for each worker type until the model's equilibrium outcomes-industrial output and population distribution-align with the 2010 data. Through this process, we calibrate city productivity and amenities (blue parts in Figure 9).

Variables such as industrial and residential land areas, population distribution across cities, and industrial outputs will be incorporated from the dataset in year 2010. Then there are only two unobservable variables left for internal calibration: city productivity and amenities. To this end, we match two model moments with empirical data: firstly, we use industrial outputs at each location, Y_{jt}, to calibrate city productivity, A_{jt}. Secondly, the population share of different skill levels (those with and without a high school degree) at each location, L_{ejt}, helps calibrate the amenities, B_{jt}. The demographic information for individuals aged 20 to 40 in each city is sourced from the China Census Data (2010). We gather data on the total area of industrial and residential land from the Urban-Rural Construction Statistical Yearbook. Additionally, industrial output information is obtained from the City Statistical Yearbook.

Algorithms to Deduce the Transition Path Beginning with the data from 2010 and applying an exogenous growth rule for fundamentals, we calculate the steady state for the subsequent period, from which we obtain the population distribution across cities, $L_{ej,T}$, and accordingly, the welfare distribution, $V_{ej,T}$. Moving backward, with the next period's population, $L_{ej,t+1}$, and welfare values, $V_{ej,t+1}$, in hand, we back-out the equilibrium outcomes of the previous period using the following steps:

1) Assume an initial group of productivity and amenity parameters, A_{jt}, B_{ej}, and import land allocation data H_{jt}, K_{jt}.

2) Set initial guesses for population and utility for Location 1: $\{L_{u1,t}, L_{s1,t}\}$ and $\{V_{u1,t}, V_{s1,t}\}$

3) Calculate inter-location population shares based on the welfare share across locations:

$$\frac{L_{ej,t+1}}{\sum_{i=1}^{N} L^c_{ej,t+1}} = \frac{\mathbb{E}[B_{ej,t+1} exp\{V_{ej,t+1}\}]^{1/\epsilon_M}}{\sum_{i=1}^{N} \mathbb{E}[B_{ej,t+1} exp\{V_{ej,t+1}\}]^{1/\epsilon_M}}$$

4) With the population and utility distribution in hand, calculate households' policy functions regarding fertility rate, education probability and migration choices (same algorithm as we detailed in the last section).

5) Continue adjusting the population and utility guess until the number of newborns and skill ratios match those observed in the next period. Finalize the according population and industrial output matrices.

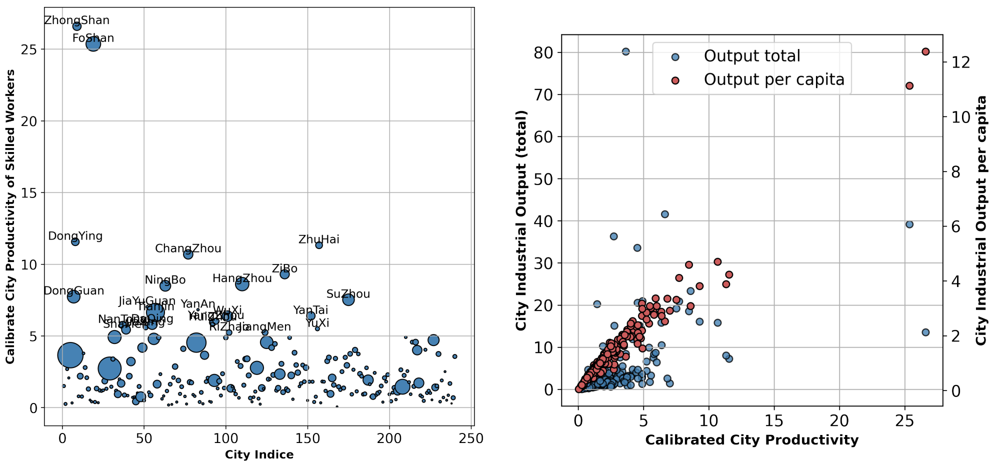
6) Adjust $\{A_{jt}, B_{ej}\}$ until the population and industrial outputs derived form the model align with the observed data.

C. *Calibration Results*

Performance of Matching Moments We first present the calibration results of productivity, A_{ejt}, in Figure 10. Figure (a) display the productivity of skilled workers in each city, , with the scatter size weighted by the city's GDP in 2010. The cities with the highest productivity are major industrial centers in China, including Zhongshan, Ningbo, and Dongguan in the south, known for industries like textiles and technology, and Dongying, Daqing, and Yuxi, which are rich in vital natural resources such as coal and steel. Panel (b) shows the relationship between calibrated city productivities and industrial output per capita in 2010. Although the calibration primarily targets total industrial output, the results align well with per capita values due to the simultaneous targeting of the population moment for city amenities.

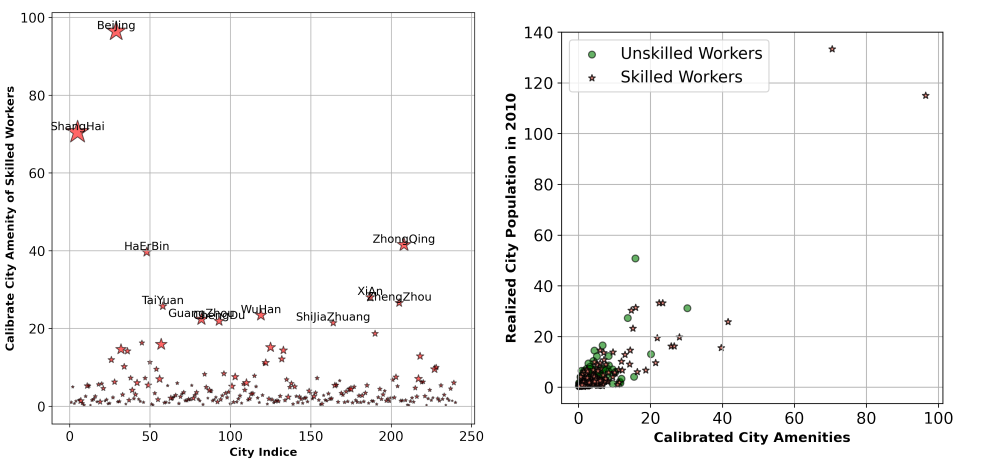
We then show the calibration results of amenities, B_{ejt}, in Figure 11. Figure (a) shows the amenities of skilled workers in each city, with the scatter size weighted by the city's urban population in 2010. It is evident that cities with the highest amenities are major Chinese cities with large populations, such as Beijing, Shanghai, Nanjing, and Guangzhou. Panel (b) illustrates the relationship between the calibrated amenities of cities and their population distribution in 2010, the target period. This relationship fits well, aligning closely with the 45-degree line.

Figure 10. Calibrated Locational Productivity



(a) Productivity Distribution (b) Fitted with Industrial Outputs

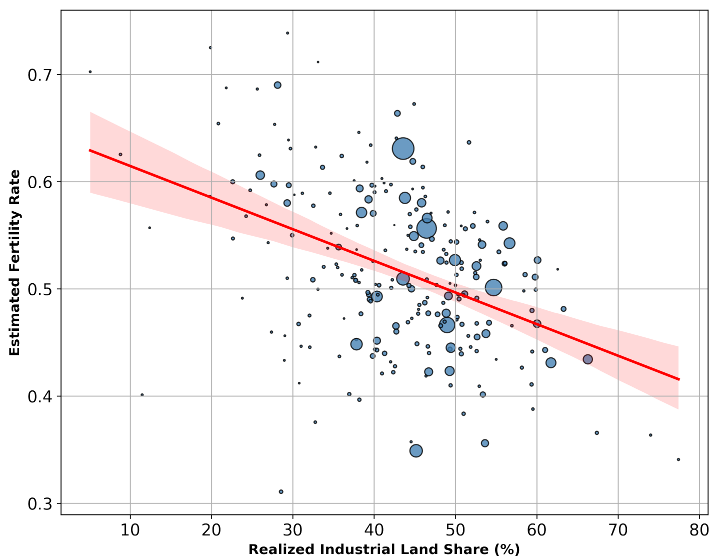
Figure 11. Calibrated Amenity



(a) Amenity Distribution (b) Fitted with Populations

Validation with Untargeted Moments With the calibrated productivity and amenities, we can now calculate the fertility rate for each city using the model and illustrate its correlation with the real-world industrial land share in Figure 12. A negative correlation between industrial land share and fertility rate is still observed, which is consistent with the pattern we described in the third stylized fact of the empirical section above (Figure 5-(b)), *that the oversupply of local industrial land is negative-correlated with lower fertility rates.* This finding is particularly critical as it was not targeted during the calibration process, demonstrating that the model aligns well with the observed data.

FIGURE 12. ESTIMATED FERTILITY RATE

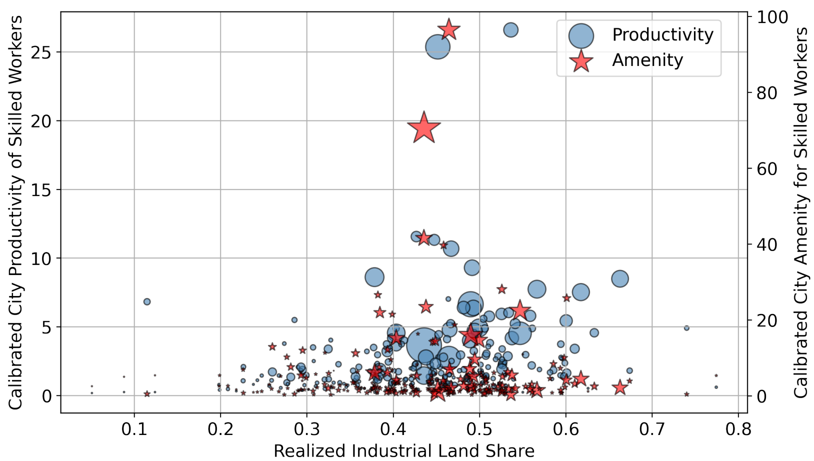


Notes: This figure shows the correlation between the real-world industrial land share and the model estimated fertility rate in each city.

We then illustrate the relationship between the calibrated productivity and amenities of cities and their realized land allocation in Figure 13. This analysis is used to validate my second empirical observations on the geographical distribution of price gaps (Figure 4), *where a wider price gap is observed in more developed regions.* In the empirical section, we used the distance to the nearest port as a proxy for city productivity, as local productivity is not directly observable and other potential productivity indicators could be endogenous to land allocation. With calibrated productivity now available, we am now able to validate this relationship using the calibrated productivity and realized land allocation, represented by the blue points in Figure 13. In addition, the relationship between industrial land and amenities appears less intensive but still significant, as shown by the red stars in Figure 13.

To more clearly illustrate the relationship among these three variables, we present a heat map of the industrial land share in Figure 14. The axes are defined with calibrated productivity on the horizontal and amenities on the vertical, where the color gradient from lighter to darker indicates an increase in industrial land share. We first rank the calibrated productivity of the 240 cities in my sample from highest to lowest and then divide them into ten groups, with each group containing twenty-four cities. These groups are further subdivided into eight subgroups based on their amenities, resulting in each subgroup containing three cities. We then calculate the average industrial land share for each entry and represent these averages using a color gradient from lighter to darker. The heat map clearly shows that as productivity increase, the industrial land share tends to increase, yet this trend is not that critical for amenity.

FIGURE 13. CALIBRATED CITY PRODUCTIVITY AND AMENITY WITH REALIZED LAND ALLOCATION



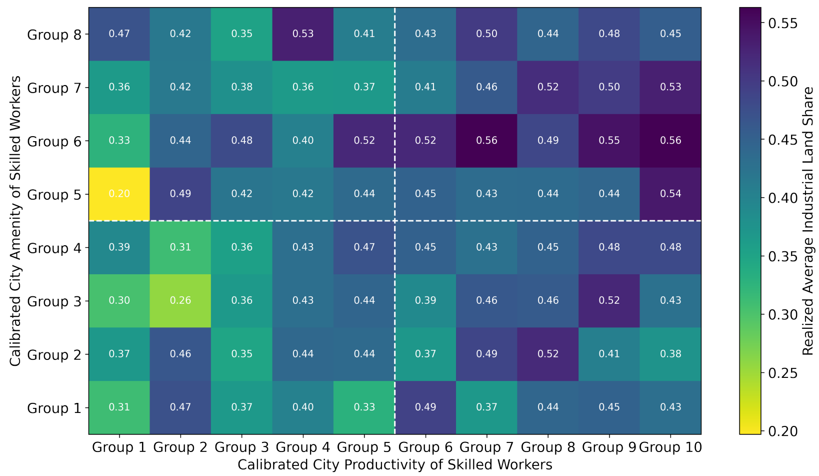
VII. Counterfactual Analysis

A. Comparison across Time

We first compare the estimated fertility rate distribution along the transition path in Figure 15, where the year 2010 uses land allocations from the data and implements the One Child Policy with a fine of $f = 0.1594$. By contrast, the year 2020 maintains the same land allocations but assumes a transition to a steady state, where the One Child Policy fine is abolished ($f = 0$), and productivity increases by 7% from 2010.[17] Two patterns emerge from this figure that can be attributed to the abolition of the One Child Policy: first, there is an average

[17] According to the estimation from the World Bank Group (Brandt et al., 2020), the labor productivity growth in China slowed down following the global financial crisis in 2008. Total factor productivity (TFP)

Figure 14. Calibrated City Productivity and Amenity with Realized Land Allocation



Notes: This is a heat map of industrial land share grouped by the calibrated city productivity and amenity. We first rank the calibrated productivity of the 240 cities in my sample from highest to lowest and then divide them into 10 groups, with each group containing 24 cities. These groups are further subdivided into 8 subgroups based on their amenities, resulting in each subgroup containing 3 cities. We then calculate the average industrial land share for each entry and represent these averages using a color gradient from lighter to darker.

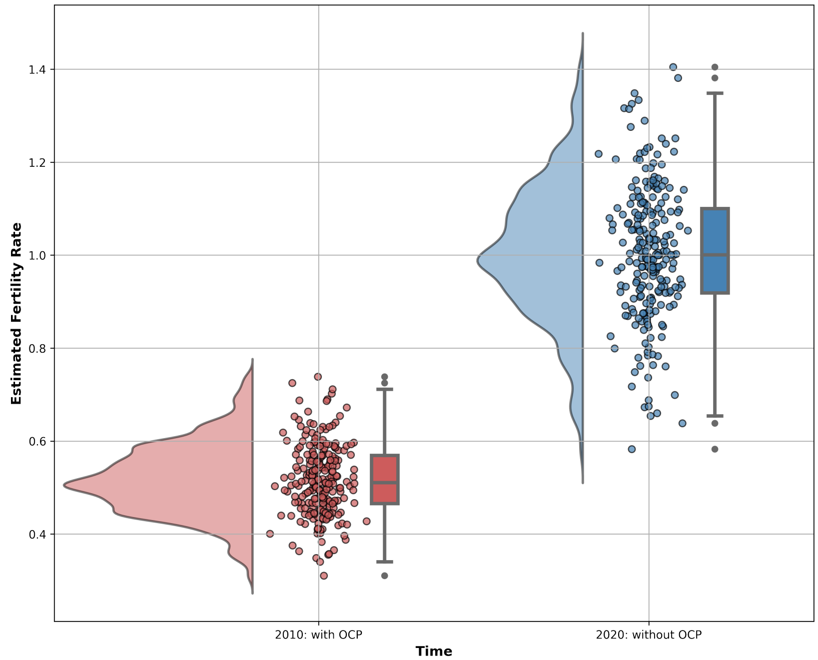
increase in the aggregate fertility rate from 2010 to 2020. Second, the variations across cities become more pronounced after the removal of the fine, indicating that the impacts of land allocation and housing prices are intensified without the One Child Policy fine. These patterns validate our simulation results shown in Figure 7 after bringing the model to empirical data and taking into the calibrated productivity values.

B. *Comparison across Policies*

We then compare the estimated fertility rate distributions for the year 2010 under various counterfactual policies. We chose to compare the outcomes in year 2010 rather than long-term steady state outcomes in 2020, because the average fertility rate in steady states would always converges to one, rendering comparisons across different policies trivial. Therefore, targeting the population distributions in steady states under several different counterfactual policies, we backup the equilibrium outcomes in the transition path in 2010.

growth decreased from 2.8 percent per year in the decade before the crisis to just 0.7 percent afterwards. Using this estimate, we calculate the productivity growth rate over ten years as $(1 + 0.7\%)^{10} = 7.22\%$. As an adjustment converging to the simulated steady state in 2020, we assume that the productivity growth is slightly higher, at 10 percent over the decade.

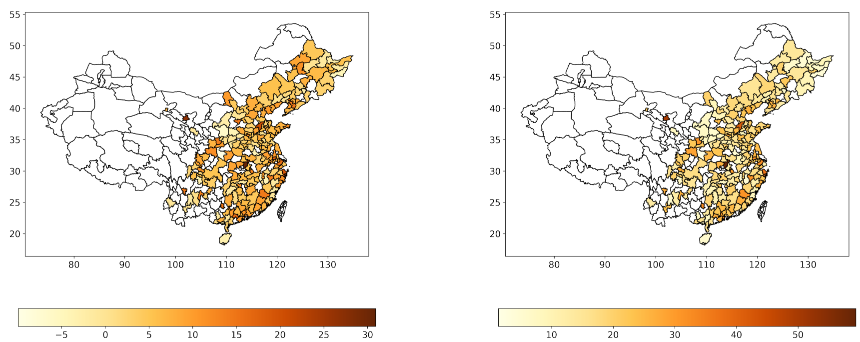
FIGURE 15. ESTIMATED FERTILITY RATE ACROSS YEARS



Land Policy After calibrating city amenities and productivity, and targeting the expected utility for children in steady states, we compare the "Realized Land" allocation in the real world with a theoretical "Free Land Market" scenario where cities adjust land shares until the prices of industrial and residential land are equal in each city. Since this comparison is based on the equilibrium outcomes observed in the transition path for the year 2010, the One Child Policy was still in effect, and it only shows the marginal effects of land policies. Figure 16 display the geographical distribution of changes in real income and fertility rates under this transition. Almost all cities can benefit in real income following the transition to a free land market, and fertility rates in all cities are also expected to rise.

Specifically, as shown in Table 3, under the implementation of the One Child Policy, shifting from the current land allocation to a free land market could increase the fertility rate from 0.52 to 0.6, a difference of 0.08. Notably, under the One Child Policy, the observed fertility rate in the benchmark scenario is 0.52, which is significantly below the natural fertility rate needed for population stability, 1.01 in the steady state. Therefore, shifting to a free land market could potentially help China address the fertility rate gap by 16.33%, which is, $(0.6 - 0.52)/(1.01 - 0.52) = 16.33\%$. Furthermore, keeping the One Child Policy, after shifting to the free land market, the real income of residents can increase by 5.43% ($= (0.97 - 0.92)/0.92$), and the industrial output can also increase by

Figure 16. From the Realized Land to a Free Land Market: Geographical Distribution of Real Income Changes and Fertility Rate



(a) Real Income Changes: Percentage (b) Fertility Rate Changes: Percentage

Notes. This figure displays the geographical distribution of real income changes and fertility rate when shifting from the realized land regime to a free land market. The "Realized Land" takes the real-world land allocation in each city from the data. The "Free Market" scenario simulates a theoretical market equilibrium where the price of industrial land equals that of residential land in each city.

17.57% (= (488.31 − 415.32)/415.32).

Population Policy We then examine the outcomes of several counterfactual scenarios with and without population control.

Figure 17 first displays the aggregate fertility rates in these counterfactual scenarios. It is not surprising to find that fertility rates would increase when either land market or population control policies is relaxed. More specifically, from Table 3, maintain the realized land and compare the fertility rate with and without the One Child Policy, the fertility rate in China could increase 0.51 (= 1.03−0.52). Keep all other conditions the same, if the government lift the One Child Policy and let market force decide the land allocation, the aggregate fertility rate in China could increase 0.5 (= 1.02 − 0.52).

However, when examining the birth rates of different child types in Figure 18, it becomes apparent that this increase primarily stems from a higher birth rate of "Lower-Education Children", suggesting a decrease in the skill ratio in counterfactual scenarios. This is because these policy relaxations would reduce the costs of living and childrearing, with the reduction being relatively larger for lower-educated children. For instance, if the childrearing cost is two for a lower-education child and four for a higher-educated one, a reduction of one due to policy relaxation would decrease the cost by 50% for lower-education children, but only by 25% for higher-education children. Meanwhile, the expected marginal

Table 3—Results of Counterfactual Exercises

	Benchmark	**Steady State**	**Counterfactuals in 2010**		
	Realized Land with OCP	SteadyState NO OCP	FreeLand with OCP	RealizedLand NO OCP	FreeLand NO OCP
Mean(Fertility Rate)	0.52	1.01	0.60	1.03	1.02
Mean(Skill Ratio)	0.39	0.32	0.45	0.34	0.34
Mean(Housing Price)	3.35	1.89	2.42	1.72	1.50
Mean(Industrial Land Price)	0.93	0.52	2.53	0.47	1.50
Mean(Welfare of Unskill)	8.06	8.52	7.96	8.40	8.25
Mean(Welfare of Skill)	8.73	9.19	8.63	9.07	8.92
Mean(Wage of Unskill)	1.20	1.39	1.09	1.28	1.15
Mean(Wage of Skill)	1.80	2.09	1.64	1.91	1.72
Mean(Efficient Labor)	535.00	338.33	694.09	278.39	425.93
Mean(Industrial Outputs)	415.32	274.16	488.31	227.38	311.32
Mean(Housing Service)	54.89	93.72	69.52	77.54	107.25
Mean(Real Income)	0.92	1.16	0.97	1.16	1.15

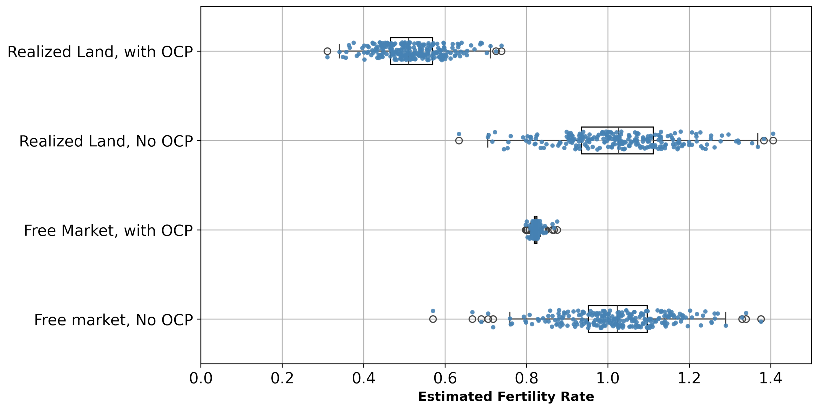
Notes. The "Baseline" takes the real-world land allocation in each city from the data. The "Steady State" represents the predicted outcomes for the year 2020, assuming the One-Child Policy had been canceled and the economy enters a steady state. The "FreeLand" scenario keeps the one child policy but simulates a theoretical market equilibrium where the price of industrial land equals that of residential land in each city. The "DoubleHouse" scenario keeps the One Child Policy but explores the effects of doubling the residential land area in each city. The "No OCP" scenario removes the One-Child Policy fine but keeps the real-world land allocation. The "Double Edu" scenario is the case where local governments double the funding of public education.

payoff of education, or skill premium, remains unchanged across counterfactual senarios. Technically, this static condition arises in my model because there is a complete substitution between skilled and unskilled labor (as shown in Equation 4), making the skill premium exogenous to align with empirical data. Therefore, this result should be better interpreted as the marginal effects of children rearing cost reducation in a partial equilibrium, exemplifing the "Quantity-Quality" trade-off inherent in family-planning decisions.

Education Policy To stimulate increased investment in children's education, we revisit the counterfactual analysis above, this time enhancing the public education funding mechanism. Specifically, we increase the public education parameter τ_{e1} from 0.05 to 0.1, representing a scenario where local governments increase the efficiency of public education service, or mathematically, equivalent to the case that governments spend a larger portion of land revenue to public education expenditures.

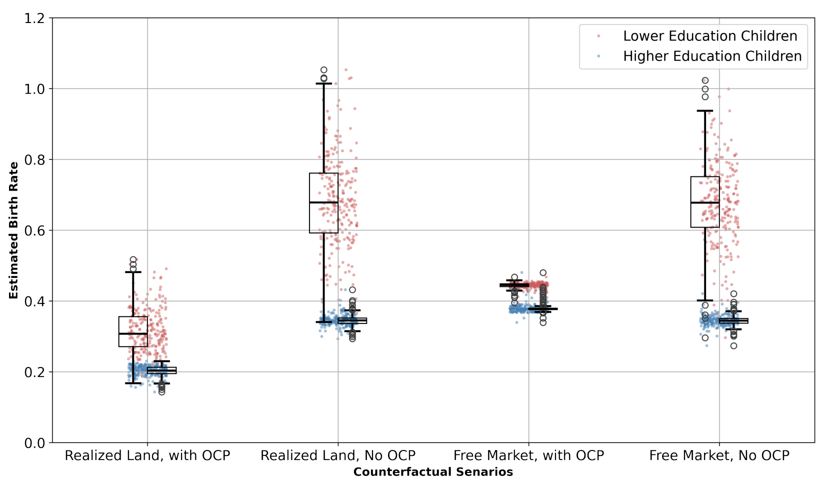
As illustrated in Table 4, for each land allocation scheme–"Realized Land," "Free Land," and "Double Housing"–we compare the long-run distributions of fertility rate and skill ratio in the steady state. The "Low Public Educ" scenario corresponds to $\tau_{e1} = 0.05$, while the "High Public Educ" scenario corresponds to $\tau_{e1} = 0.1$. The results indicate that both the population and the skill ratio would increase when governments invest more on public education expenditure. Specifically, under the realized land scheme, when governments lift the One Child Policy, increasing the public service efficiency could potentially increase the long-

Figure 17. Estimated Fertility Rate in Counterfactual Scenarios



Notes. The "Realized Land" takes the real-world land allocation in each city from the data. The "Free Market" scenario simulates a theoretical market equilibrium where the price of industrial land equals that of residential land in each city.

Figure 18. Estimated Children Education in Counterfactual Scenarios



Notes. The "Realized Land" takes the real-world land allocation in each city from the data. The "Free Market" scenario simulates a theoretical market equilibrium where the price of industrial land equals that of residential land in each city.

run skill ratio by 6.67%((0.285 − 0.266)/0.285). In summary, this model identifies three key policy levers that influence both the fertility rate and the skill ratio of children: the One-Child Policy, land allocation, and public education funding.

Table 4—Results of Counterfactual Exercises with Public Education Expenditure

	Total Population		Skill Ratio	
	Low Public Educ	High Public Educ	Low Public Educ	High Public Educ
Realized Land	29179.738420	30212.388312	0.266389	0.284808
Free Land	44320.656919	45846.090582	0.265299	0.277977
Doubling Housing	58264.011725	59968.889190	0.265462	0.280781

Notes. The "Realized Land" takes the real-world land allocation in each city from the data. The "Free Land" scenario keeps the one child policy but simulates a theoretical market equilibrium where the price of industrial land equals that of residential land in each city. The "Double House" scenario keeps the One Child Policy but explores the effects of doubling the residential land area in each city. The " High Public Educ" scenario is the case where where we increase the coefficient of education cost on public education expenditure τ_{e1j} from 0.05 to 0.1.

VIII. Concluding Remarks

Population decline has been a common problem throughout history in many countries, particularly in developed nations such as Japan, Korea, and several European countries. My project explains the dramatic population decline in recent years in China from the perspective of political and spatial economics, attributing it as an unintended consequence of local governments' land allocation decisions. We provide a unified spatial-OLG framework to capture the interplay between government land allocation, population controls, and public education expenditures on household family planning decisions. Additionally, my work contributes to the existing literature by integrating population growth into a spatial model.

My quantitative results are best interpreted as partial equilibrium estimations of land allocation, as they abstract from an explicit analysis on governments' land allocation decisions. Previous literature offers several explanations for the motivations of pro-industrial land allocation in China, including corruption (Cai, Henderson and Zhang, 2013), fiscal revenue maximization (He et al., 2022), and spatial competition to bid for firms and promote local economic growth (Tao et al., 2010; Henderson et al., 2022). My project significantly differs from theirs by treating governments' local land allocation as given and exploring the dynamic effects on households' decisions, focusing primarily on the "Consequence" side. The reason for this focus is to strike a balance between tractability and complexity, given the computational challenges of modeling population growth in an endogenous spatial model. [18]

Although the state-owned land ownership system in China is unique and differs from that in many other countries, land-use restrictions are common in numerous nations. This framework can be extended to a broader context to quantify the impact of governments' land policies on household behavior. For example, it would be valuable to conduct a cross-national comparison by examining land market behavior in other countries, investigating whether a similar price gap between industrial and residential land exists, and exploring the possible reasons, such as zoning policies.

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[18] My another project, co-authored with Qiaohairuo Lin from Vanderbilt University, focuses on the endogenous land decisions driven by local governments aiming to maximize industrial output, addressing primarily the "Cause" side. We explore the non-cooperative Nash equilibrium of government competition without considering the long-run effects on human capital. For the full text, please see this link: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4867308.

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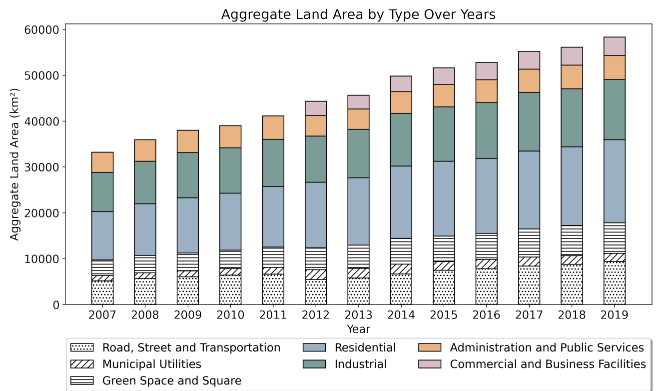
Appendix I. Data Details

To investigate urban land allocation in China, we employ two datasets. The first dataset, "China Urban Construction Statistical Yearbooks" from the Ministry of Housing and Urban-Rural Development of China, represents the annual "STOCK" of urban land and helps illustrate the aggregate land allocation patterns and quantify the model. The second dataset, used in the empirical analysis section, consists of web-scraped data on urban land transactions over the past decade and represents the "FLOW" of urban land. This dataset records the unit price of each land parcel and is critical to identifying the urban land misallocation in the empirical section.

Stock Data From Yearbooks Table A1 summarizes the area of industrial and residential land areas across years. First, both types of land are expanding due to China's ongoing urbanization, with the proportion of industrial land slightly decreasing but remaining above 32%. We illustrate the quantiles of each land type and their ratio over time in Figure A3. The variations in urban land areas across different periods can also be attributed to changes in administrative boundaries, such as annexing or ceding small towns, and shifts in statistical criteria. For example, the noticeable deviation in the growth trend of industrial land area in 2012, shown in Figure A3, is likely due to the implementation of new national land use and planning standards (GB 50137-2011). Furthermore, we mapped the industrial land area ratios in Figure **??**, where deeper colors indicate higher industrial land ratios, typically concentrated along the coastline and China's most developed regions.

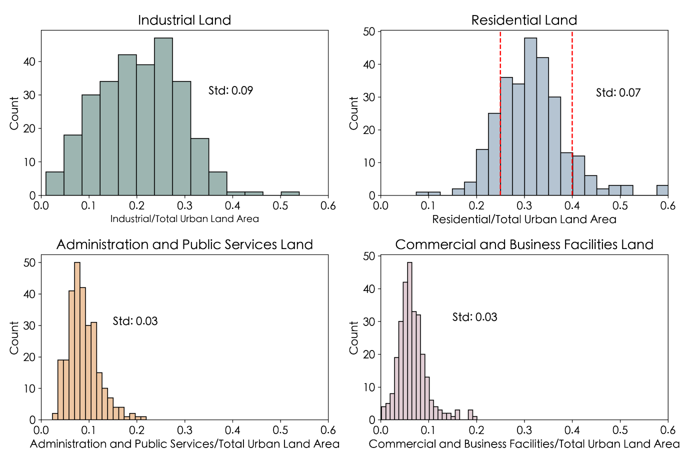
Flow Data From Transaction Records Since 2007, all industrial urban land transactions in China have been required to be auctioned and posted publicly on the website of the Ministry of Land and Resources. We web-scrapped all land transaction records from 2007 to 2019, which contain 2,243,010 land transactions, including 501,289 industrial and 1,115,517 residential or commercial land sales. Each transaction record details the characteristics of the land parcels, such as their quality (government-evaluated and categorized into several ranks before auction), area (measured in acres), source (whether the land is newly acquired urban land or existing urban land), and location (calculated as the distance from the land parcel to the city government and the geographical center of the county-level administrative district). It also includes information on transaction methods, prices, and pre-determined land usage. The summary statistics of the dataset are presented in Tables A2 and A3.

FIGURE A1. AGGREGATE URBAN LAND AREA BY USAGES AND YEARS (UNIT: km^2)



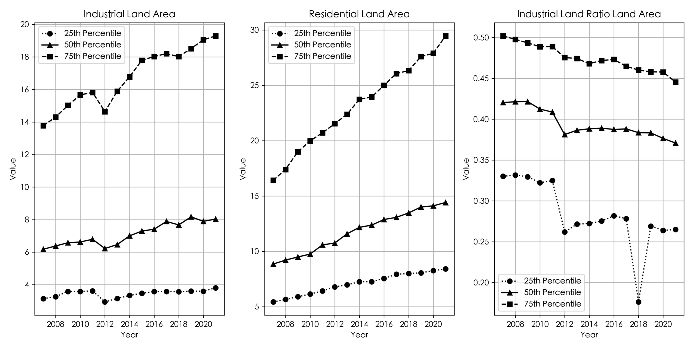
Notes: The data was obtained from the Urban Construction Statistical Yearbook of China (2007 to 2019) and was published by the Ministry of Housing and Urban-Rural Development of China.

FIGURE A2. DISTRIBUTION OF LAND AREA SHARE IN 2019 ACROSS CITIES



Notes: The data was obtained from the Urban Construction Statistical Yearbook of China (2007 to 2019) and was published by the Ministry of Housing and Urban-Rural Development of China.

Figure A3. Evolution of Land Area and Ratio in Yearbook Data



Notes: Data source is the Ministry of Housing and Urban-Rural Development of China, Urban Construction Statistical Yearbook (2007 - 2019). Industrial Land Ratio is calculated as the ratio between industrial land area and the summation of industrial land area and residential land area.

Table A1—Summary Statistics of Statistics Yearbook Data (2007-2021)

	Industrial Land Area		Residential Land Area		Industrial Land Ratio		Number of
Year	Mean	SD	Mean	SD	Mean	SD(×100)	Observations
2007	15.182	3.639	22.698	6.399	0.370	0.542	610
2008	16.170	3.716	24.681	7.144	0.368	0.541	611
2009	17.999	4.656	26.084	7.371	0.369	0.539	612
2010	18.816	5.361	26.770	7.459	0.362	0.536	610
2011	19.353	5.883	28.519	8.018	0.356	0.539	609
2012	19.866	5.468	31.643	8.155	0.324	0.629	607
2013	20.864	5.747	32.651	8.538	0.329	0.598	608
2014	22.444	6.249	34.910	9.227	0.328	0.588	615
2015	23.421	6.655	36.251	9.791	0.331	0.596	616
2016	23.818	6.745	36.064	9.862	0.333	0.599	616
2017	25.116	6.739	37.937	9.963	0.332	0.582	614
2018	24.817	6.931	38.058	10.587	0.327	0.582	613
2019	25.713	7.166	39.888	10.979	0.327	0.579	614
2020	26.392	8.081	39.965	11.112	0.326	0.599	613
2021	26.367	8.511	41.122	11.709	0.323	0.574	612

Notes: Data source is the Ministry of Housing and Urban-Rural Development of China, Urban Construction Statistical Yearbook (2007 - 2019). Industrial Land Ratio is calculated as the ratio between industrial land area and the summation of industrial land area and residential land area.

Table A2—Summary Statistics of Land Transaction Database (2007-2019)

		Freq.	Percent	
Number of Transactions	Urban	802,864	35.79	
	Rural	1,440,146	64.21	
Urban Land Transactions				
Land source	New Construction Sites	344,598	42.92	
	New Construction Sites (from Stock Pool)	98,137	12.22	
	Existing Construction Sites	360,129	44.86	
Transaction Saleway	Allocation	251,004	31.26	
	Negotiation	247,625	30.84	
	Auction	38,247	4.76	
	Bidding	4,036	0.5	
	Listing	261,952	32.63	
Land Type	Residential Land	275,432	34.57	
	Industrial Land	161,898	20.32	
	Commercial Land	103,022	12.93	
	Transportation Land	84,569	10.61	
	Public Admin & Service Land	127,048	15.95	
	Other Types	44,782	5.62	
Other Characteristics	**Mean**	**Std.**	**Min**	**Max**
Area of Land Parcel	4.167	80.320	0	42559
Total Price of Land Parcel	16,123.450	5,943,619	0	3.62E+09
Unit Price Per Hectares	1,136.755	2,324.461	0	12750.02
FAR Lower Bound	0.831	0.790	0	5
FAR Upper Bound	1.731	1.473	0	7
Distance to City Center	40.360	153.878	0	2941.959

Notes: This table describes the public land transaction records from the Ministry of Land and Resources via web scraping. This dataset contains 2,243,010 land transactions, including 501,289 industrial and 1,115,517 residential-commercial land sales.

Table A3—Summary Statistics of Land Transaction Database 2

	New Construction Sites		New Sites from Stock Pool		New Construction Sites	
Transaction Saleway	**Freq.**	**Percent**	**Freq.**	**Percent**	**Freq.**	**Percent**
Allocation	151,556	43.98	36,812	37.51	62,636	17.39
Negotiation	20,549	5.96	24,701	25.17	202,375	56.2
Auction	19,303	5.6	5,515	5.62	13,429	3.73
Bidding	1,818	0.53	475	0.48	1,743	0.48
Listing	151,372	43.93	30,634	31.22	79,946	22.2
	New Construction Sites		**New Sites from Stock Pool**		**New Construction Sites**	
Land Usage	**Freq.**	**Percent**	**Freq.**	**Percent**	**Freq.**	**Percent**
Residential Land	53,528	15.56	35,758	36.44	186,146	52.5
Industrial Land	103,028	29.94	14,571	14.85	44,299	12.49
Commercial Land	35,624	10.35	11,281	11.5	56,117	15.83
Transportation Land	58,760	17.08	13,053	13.3	12,756	3.6
Public Admin & Service Land	73,731	21.43	16,446	16.76	36,871	10.4
Water Facilities Land	1,700	0.49	361	0.37	471	0.13
Public Rental Housing Land	1,536	0.45	347	0.35	1,478	0.42
Low-Rent Housing Land	1,855	0.54	925	0.94	1,512	0.43
Affordable Housing Land	9,985	2.9	4,759	4.85	12,657	3.57
	Residential Land		**Industrial Land**		**Commercial Land**	
Transaction Saleway	**Freq.**	**Percent**	**Freq.**	**Percent**	**Freq.**	**Percent**
Allocation	15,158	5.5	3,371	2.08	2,259	2.19
Negotiation	157,296	57.11	30,610	18.91	37,705	36.6
Auction	21,793	7.91	6,574	4.06	8,679	8.42
Bidding	1,728	0.63	1,082	0.67	1,068	1.04
Listing	79,457	28.85	120,261	74.28	53,311	51.75
	Residential Land		**Industrial Land**		**Commercial Land**	
Land Source	**Freq.**	**Percent**	**Freq.**	**Percent**	**Freq.**	**Percent**
New Construction Sites	53,528	19.43	103,028	63.64	35,624	34.58
New Sites from Stock Pool	35,758	12.98	14,571	9	11,281	10.95
Existing Construction Sites	186,146	67.58	44,299	27.36	56,117	54.47

Notes: This table describes the public land transaction records from the Ministry of Land and Resources via web scraping. This dataset contains 2,243,010 land transactions, including 501,289 industrial and 1,115,517 residential-commercial land sales.

Appendix II. Robustness Checks on Industrial Discounts

In July 2007, the central government of China enforced public auctions for industrial land transactions, which led to a big shift in the transaction format of land. During the main sample periods from 2007 to 2019, 47.55% of commercial and residential lands are sold by public auctions, while only 13.26% of industrial lands are sold by negotiation. This regulation can reduce the local government's direct control over the price of land, making it less convincing to attribute the industrial discount to the transaction format of "negotiation". However, local governments maintain the discretion power in determining the supply of each land type, which could still lead to a price difference. For example, local governments can choose to restrict the quota of residential land but supply more industrial lands. Therefore, if all lands were auctioned without prior designations of land use (industrial or non-industrial land), then auctions should give the same price for both lands.

In Table A1, we refine the sample to focus exclusively on transactions via public auctions, excluding land designed for other usages, such as public service, transportation, and water facilities. This narrowed comparison between industrial and residential land transactions reveals a persistent industrial discount, ranging from 0.34 ($= exp(-1.071)$) to 0.167 ($= exp(1.792)$). Therefore, local governments can manipulate prices by adjusting the allocation of land quotas available for auction. To manage variations from the demand side, we categorized buyers into four groups: firms, governments, urban construction investment enterprises, and others. Submarkets with extreme concentrations (where a single agent holds more than 10% of land area) or with scarce samples (fewer than 100 transactions) are excluded from the analysis. The results are shown in Table A2.

Table A1— Robustness Check 1: Subsamples of TWO lands via public auctions

VARIABLES	(1) $log(P_{ict}/floor)$	(2) $log(P_{ict}/floor)$	(3) $log(P_{ict})$	(4) $log(P_{ict}/floor)$	(5) $log(P_{ict}/floor)$	(6) $log(P_{ict})$
$IndDummy_{ict}$	-1.792***	-1.071***	-1.407***	-3.386***	-2.831***	-3.168***
	(-85.987)	(-56.323)	(-74.022)	(-19.221)	(-16.161)	(-18.082)
$IndDummy_{ict} \times Dist_c$				0.130***	0.143***	0.143***
				(9.096)	(10.174)	(10.174)
$log(dcity_{ict})$	-0.179***	-0.156***	-0.156***	-0.178***	-0.156***	-0.156***
	(-32.938)	(-29.616)	(-29.616)	(-32.776)	(-29.806)	(-29.806)
$log(area_{ict})$	0.001	0.013**	0.013**	-0.003	0.007	0.007
	(0.187)	(2.499)	(2.499)	(-0.721)	(1.464)	(1.464)
$log^2(area_{ict})$	-0.009***	-0.009***	-0.009***	-0.010***	-0.010***	-0.010***
	(-4.311)	(-4.009)	(-4.009)	(-4.645)	(-4.366)	(-4.366)
Other Characteristics	Y	Y	Y	Y	Y	Y
City X Year FE	Y	Y	Y	Y	Y	Y
Observations	147,065	152,081	152,081	147,065	152,081	152,081
R-squared	0.785	0.657	0.707	0.788	0.662	0.711

Notes. This table keeps the subsamples of industrial land and residential-commercial land transactions and excludes all transactions via negotiation or allocation. Control variables in each regression contain the format of transactions, the maximum floor area ratio, land quality rank, and the source of land. All standard errors are clustered into the level of city-year.

Table A2—Robustness Check 2: Controlling Market Extremes

VARIABLES	(1) $log(P_{ict}/floor)$	(2) $log(P_{ict}/time)$	(3) $log(P_{ict})$	(4) $log(P_{ict}/floor)$	(5) $log(P_{ict}/time)$	(6) $log(P_{ict})$
$IndDummy_{ict}$	-1.709***	-1.011***	-0.675***	-3.439***	-2.907***	-2.570***
	(-76.782)	(-50.520)	(-33.709)	(-19.710)	(-16.821)	(-14.874)
$IndDummy_{ict} \times Dist_c$				0.141***	0.154***	0.154***
				(10.037)	(11.196)	(11.196)
$log(dcity_{ict})$	-0.179***	-0.156***	-0.156***	-0.178***	-0.156***	-0.156***
	(-31.277)	(-28.224)	(-28.224)	(-31.167)	(-28.409)	(-28.409)
$log(area_{ict})$	-0.004	0.010**	0.010**	-0.009**	0.004	0.004
	(-0.830)	(2.162)	(2.162)	(-1.978)	(0.860)	(0.860)
$log^2(area_{ict})$	-0.009***	-0.008***	-0.008***	-0.009***	-0.009***	-0.009***
	(-3.815)	(-3.703)	(-3.703)	(-4.144)	(-4.044)	(-4.044)
Other Characteristics	Y	Y	Y	Y	Y	Y
City - Year FE	Y	Y	Y	Y	Y	Y
Observations	129,462	132,887	132,887	129,462	132,887	132,887
R-squared	0.777	0.647	0.599	0.780	0.653	0.606

Notes. This table keeps only residential and industrial land transaction records, excluding all transactions via negotiation or allocation. Further robustness is checked by controlling buyer information (firms, governments, or urban construction investment enterprises) and excluding submarkets with extreme concentrations (one single agent holding more than 10% of land area) or scarce samples (less than 100 transactions. All parcel characteristics for each land sale are controlled, including the distance to the urban district center or rural county center, the leasing time left, the area of land, the rank of land quality, floor-area ratio (FAR) restrictions, the format of transactions, the source of land.

Appendix III. Empirical Results Dealing with One-Child-Policy Variations

Due to the stringent enforcement of the one-child policy, all counterfactual real fertility willingness at this period would be covered by it. To alleviate this concern, we construct a variable to capture the implementation of the "One-Child Policy" at the city level, measured as the average permit price to have a second or third child.[19] Specifically, according to García (2022), a woman i at the age a had to register her pregnancy to the local birth-planning authority and sign a "One-Child Policy contract" with the government. This contract stipulated the cost and payment method for having second or third children, and was varied across provincial governments, with payments set as either a percentage of the household's labor income or as a fixed lump sum fine:

$$\Xi_{ia} = \mathbb{1}[\text{proportional-price province}]_{ia} \times \left[\sum_{l=1}^{L_{ia}^{\text{prop}}} \beta^{l-1}(\kappa y_{ia}) \right] + \mathbb{1}[\text{lump-sum price province}]_{ia} \times \left[\sum_{l=1}^{L_{ia}^{\text{lump}}} \beta^{l-1}(\tau_{ia}) \right]$$

Here, κ_{ia} is the fraction of household income to be paid in proportional-policy provinces and τ_{ia} is the amount in lump-sum-policy provinces. β is the discount factor. Ξ_{ia} is set to zero if she was qualified for an exemption from the payments, for reasons such as the death or disability of their first child, job-related difficulties, or a lack of males in the family. Noted that this policy price estimation was based on the China Health and Retirement Longitudinal Study (CHARLES, 2017) and only covers the period from 1979-2000, we adjusted this estimation by incorporating an autoregressive (AR1 and AR3) process prediction and then aggregate this value at the city level as a measurement of "One-Child Policy" implementation, $OCPfine_c$.

At the City Level We run the following regressions at the city level to show the relationship between land allocation and fertility rate:

$$FertilityRate_c = \beta_0 + \beta_1 IndShare_c + \beta_3 OCPfine_c + \alpha_p + \varepsilon_c \quad \text{(A1)}$$

$$PopuGrowth_{ct} = \beta_0 + \beta_1 lag.IndShare_{ct} + \alpha_c + \alpha_{pt} + \varepsilon_{ct} \quad \text{(A2)}$$

First, $FertilityRate_c$ represents the average number of live births of married women at city c. $IndShare_c$ is the area share of industrial land in her city. And $OCPfine_c$ denotes the city-level permit price from the policy contract. Table A1 presents the regression results. Columns (1) to (3) show that housing prices

[19] We thank García (2022) for providing the datasets and codes for this measurement. However, all errors are my own.

significantly and negatively impact city fertility rates, even after accounting for provincial fixed effects. Meanwhile, the influence of industrial area share, though less pronounced, is still significantly negative, as indicated in columns (4) to (6). This pattern could be attributed to the multifaceted determinants of housing prices in a city, including economic circles, housing market dynamics, and financial market variations. Overall, this table consistently indicates that both housing prices and industrial area allocation negatively affect fertility rates, even after adjusting for variations in the "One-Child Policy" implementation.

Second, we utilize a city panel that includes the natural population growth rate sourced from city yearbooks from 2000 to 2019. We regress this information on the industrial land area ratio of each city, applying a one-period lag, and control for city-specific fixed effects and province-by-year fixed effects. In Column (1) of table A1, we use the whole sample from the year 2000 to 2019, finding the effects of land allocation on fertility rate to be not significant. Columns (2) and (3) separate the samples into two groups: 2000 to 2013, under the implementation of the One-Child Policy; and 2017 to 2019, when a second child was allowed nationwide. Years between 2013 and 2016 is the policy experiment period when parents who were both single children from their original families were allowed to apply for a second child. We skip this period to avoid the local variation in policy implementation during this period. We exclude the transitional period from 2013 to 2016, a time of policy experimentation where couples if both were only children from their original families, could apply for a second child. This exclusion helps to mitigate the effects of policy variation during these years. The results indicate that the effect of land allocation on population growth rates was obscured by the One-Child Policy but became significantly negative after the policy was eased. Robustness check in column (4) using the number of newborns in each city as a dependent variable shows a similar result.

At the Individual Level We then use the China National Census 2010 to run the following regressions at the individual level:

$$FertilityDummy_{ic} = \beta_0 + \beta_1 lag.IndShare_c + \beta_3 OCPfine_c + \beta_4 x_{ic} + \varepsilon_{ic} \tag{A3}$$

Here, $FertilityDummy_{ic}$ denotes whether a married woman aged between 15 and 49, living in urban area i within city c, has given birth in the year before the census survey. $lag.IndShare_c$ is the proportion of industrial land in the city c over the past three years. To address potential bias from location self-selection, we exclude individuals who have either changed their residence locations within the past five years or household registration locations (Hukou) from their birthplace. This analysis includes demographic characteristics at the individual level, denoted by x_{ic}, which comprises age, education, dummy variables indicating a minority ethnic group, agricultural Hukou status, and whether the individual has a son before. Results from linear probability regressions are presented in columns (1) and (3) of Table A2, while columns (2) and (4) detail findings from Logit regressions. For columns (3) and (4), age and education variables are converted into dummy variables as a measure of robustness. Similar to city-level regressions, we found that a city's industrial land allocation is associated with a decrease in fertility rates, even after we control the financial fine of the One-Child Policy.

Table A1— The Effects of Land Allocations on the Fertility Rate: City Level

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Cross-sectional Comparison at Year 2010						
VARIABLES: $FertilityRateofCity_c$						
	Average	AR1	AR3	Average	AR1	AR3
$HousingPrice/Wage_c$	-0.942*	-0.925*	-0.920*			
	(-1.779)	(-1.748)	(-1.745)			
$InduAreaRatio_c$				-0.003***	-0.003***	-0.003***
				(-3.396)	(-3.523)	(-3.366)
$OCPfine_c$	-0.054	-0.393	-3.144	-0.105	-0.569	-4.326
	(-0.624)	(-1.083)	(-1.225)	(-1.055)	(-1.464)	(-1.593)
Province FE	Y	Y	Y	Y	Y	Y
R-squared	0.574	0.575	0.576	0.553	0.551	0.554
Observations	250	250	250	248	248	248
Panel B: City-level Fixed Effect Regressions						
VARIABLES	$\Delta Popu_{ct}$	$\Delta Popu_{ct}$	$\Delta Popu_{ct}$	$log(NewBorn_{ct})$		
	2000-2019	2000-2013	2017-2019	2017-2019		
$lag.InduAreaRatio_{ct}$	-0.011	0.002	-0.063*	-0.0039***		
	(-1.305)	(0.276)	(-3.543)	(-2.108e+07)		
City FE	Y	Y	Y	Y		
Province-Year FE	Y	Y	Y	Y		
R-squared	0.775	0.766	0.900	0.960		
Observations	4,531	2,919	801	803		

*Notes.*This table shows the effects of land allocation on households' fertility decisions. For Panel A, FertilityRate_c is calculated by the average number of live births in 2010 among married women aged 15-49 residing in urban areas at the prefecture level. Housing_wage_c is calculated as house prices divided by the average wage of employed workers at the prefecture level, and serves as a measure of homeownership affordability for the working population in each city. OCP_Price_c captures the implementation of "One-Child Policy" in each city, measured by the average permit price for having a second or third child according to García (2022). We run cross-sectional regressions in the year 2010. Panel B displays city-level regressions controlling province-year fixed effects.

Table A2— The Effects of Land Allocations on Fertility Rate: Individual Level

VARIABLES: Fertility Dummy at Year 2010_{ic}	(1) Linear	(2) Logit	(3) Linear	(4) Logit
$lag3.InduAreaRatio_c$	-0.010**	-0.457**	-0.009**	-0.452**
	(-2.559)	(-2.074)	(-2.129)	(-2.037)
$OCPPrice_c$	0.002	0.134	0.002	0.107
	(0.665)	(0.873)	(0.691)	(0.692)
$SonDummy_{ic}$	-0.012***	-0.495***	-0.013***	-0.522***
	(-10.778)	(-10.967)	(-10.927)	(-11.621)
$MinorityDummy_{ic}$	-0.000	-0.023	-0.000	-0.014
	(-0.066)	(-0.201)	(-0.158)	(-0.120)
$AgricDummy_{ic}$	0.001	0.008	0.002*	0.099*
	(1.004)	(0.149)	(1.906)	(1.810)
Age_{ic}	-0.023***	-0.175***		
	(-27.679)	(-5.785)		
Age^2_{ic}	0.000***	-0.000		
	(25.708)	(-0.136)		
$HighSchoolDummy_{ic}$	0.000	0.096*		
	(0.341)	(1.933)		
20-24			-0.014	-0.033
			(-0.392)	(-0.105)
25-29			-0.076**	-0.768**
			(-2.074)	(-2.435)
30-34			-0.111***	-1.652***
			(-3.047)	(-5.203)
35-39			-0.126***	-2.609***
			(-3.457)	(-8.139)
40-44			-0.132***	-3.650***
			(-3.616)	(-11.073)
45-49			-0.133***	-4.036***
			(-3.637)	(-11.969)
$PrimarySchool$			0.005	0.490
			(1.468)	(1.049)
$MiddleSchool$			0.002	0.269
			(0.576)	(0.581)
$HighSchool$			0.001	0.246
			(0.404)	(0.530)
$JuniorCollege$			0.005	0.449
			(1.574)	(0.961)
$College$			0.009**	0.596
			(2.567)	(1.270)
$Postgraduate$			0.014**	0.793
			(2.389)	(1.597)
Observations	133,227	133,227	128,693	128,693
R-squared	0.044		0.043	

Notes. This table shows the effects of land allocation on households' fertility decisions at the individual level. Census data for the year 2010 is used.

Appendix IV. Derivation of Probability

We consider the following scenario for Gumbel i.i.d. shock: suppose that we have $Y_1 = X_1 + \epsilon_1$, $Y_2 = X_2 + \epsilon_2$ where X_1 and X_2 are some non-stochastic value, and ϵ's are drawn from Gumbel distribution whose cdf is

$$F(x) = e^{-e^{-\frac{x}{\sigma}}}$$

Therefore, the

1) **What is** $Prob(Y_1 < Y_2)$**?**

Let $d = X_2 - X_1$, then we have

$$\begin{aligned} Pr(Y_1 - Y_2 < 0) &= Pr(\epsilon_1 - \epsilon_2 < d) \\ &= \int_{-\infty}^{\infty} dF(x_2) \int_{-\infty}^{x_2+d} dF(x_1) \\ &= \int_{-\infty}^{\infty} F(x_2 + d) dF(x_2) \end{aligned}$$

We plug in everyting in (and use x to denote x_2 for simplicity) to have:

$$Pr(Y_1 - Y_2 < 0) = \int_{-\infty}^{\infty} \frac{1}{\sigma} e^{-\frac{x}{\sigma}} \cdot e^{-e^{-\frac{x}{\sigma}}} \cdot e^{-e^{-\frac{x+d}{\sigma}}} dx$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sigma} e^{-\frac{x}{\sigma}} \cdot e^{-e^{-\frac{x}{\sigma}} - e^{-\frac{x+d}{\sigma}}} dx$$

Let $y = e^{-\frac{x}{\sigma}}$, then we have

$$Pr(Y_1 - Y_2 < 0) = \int_{0}^{\infty} e^{-y(1+e^{-\frac{d}{\sigma}})} dy = \frac{1}{1 + e^{-\frac{d}{\sigma}}}$$

As $d = X_2 - X_1$, we can rewrite it as

$$Pr(Y_1 < Y_2) = \frac{exp(X_2/\sigma)}{exp(X_2/\sigma) + exp(X_1/\sigma)}$$

2. **What is** $\mathbb{E}[max(Y_1, Y_2)]$**?**

Similarly, we consider $d = X_2 - X_1$ and what we need to calculate is $X_1 + \mathbb{E}[\max(\epsilon_1, \epsilon_2 + d)]$. Let $X = [\max(\epsilon_1, \epsilon_2 + d)$, we can firstly specify the distribution of X:

$$
\begin{aligned}
P(X < x) &= P(\epsilon_1 < x)P(\epsilon_2 < x - d) \\
&= e^{-e^{-\frac{x}{\sigma}}} e^{-e^{-\frac{x-d}{\sigma}}} \\
&= e^{-e^{-\frac{x}{\sigma}}(1+e^{\frac{d}{\sigma}})}
\end{aligned}
$$

Then we have

$$
\begin{aligned}
\mathbb{E}[X] &= \int_{-\infty}^{\infty} x d e^{-e^{-\frac{x}{\sigma}}(1+e^{\frac{d}{\sigma}})} \\
&= \frac{1+e^{\frac{d}{\sigma}}}{\sigma} \int_{-\infty}^{\infty} x e^{-\frac{x}{\sigma}(1+e^{\frac{d}{\sigma}})} e^{-e^{-\frac{x}{\sigma}}(1+e^{\frac{d}{\sigma}})} dx
\end{aligned}
$$

Let $y = e^{-\frac{x}{\sigma}}(1 + e^{\frac{d}{\sigma}})$. Then we have

$$
\begin{aligned}
x &= -\sigma log y + \sigma log(1 + e^{\frac{d}{\sigma}}) \\
dy &= -\frac{1+e^{\frac{d}{\sigma}}}{\sigma} y dx
\end{aligned}
$$

Plug them back, we have

$$
\begin{aligned}
\mathbb{E}[X] &= \int_{0}^{\infty} [-\sigma log y + \sigma log(1 + e^{\frac{d}{\sigma}})] e^{-y} dy \\
&= \sigma log(1 + e^{\frac{d}{\sigma}}) \underbrace{\int_0^{\infty} e^{-y} dy}_{1} - \sigma \underbrace{\int_0^{\infty} log y e^{-y} dy}_{Constant}
\end{aligned}
$$

Let Γ denote that constant, then we have

$$
\mathbb{E}[X] = \sigma log(1 + e^{\frac{d}{\sigma}})
$$

Therefore, we have

$$
\begin{aligned}
\mathbb{E}[max(Y_1, Y_2)] &= X_1 + \mathbb{E}[\max(\epsilon_1, \epsilon_2 + d)] \\
&= X_1 + \sigma log(1 + e^{(X_2 - X_1)/\sigma}) \\
&= \sigma log(e^{X_1/\sigma} + e^{X_2/\sigma})
\end{aligned}
$$

Appendix V. Uniqueness of the Steady State

Here we discuss the uniqueness of steady state by two steps. First, at the cross-sectional level, we prove that the spatial equilibrium is unique. Specifically, given initial populations (L_{u1t}, L_{s1t}) and utilities (V_{u1t}, V_{s1t}) for location one, there exists only one corresponding population vector (L_{ujt}, L_{sjt}) for any other location j. Consequently, the aggregate national population is unique. Secondly, at the cross-time level, we prove that at the aggregate level, considering the nation as a whole, the solution to the steady-state condition-where the population in the next period remains the same as in the current period-is also unique.

Uniqueness of Solution to Migration Condition From Equation 11, in any period, in a spatial equilibrium, the population distribution across cities satisfies:

$$\frac{\mathbb{E}[B_{u1} exp\{V_{u1}\}]^{1/\epsilon_M}}{\mathbb{E}[B_{uj} exp\{V_{uj}\}]^{1/\epsilon_M}} = \frac{L_{u1t}}{L_{ujt}}$$
$$\frac{\mathbb{E}[B_{s1} exp\{V_{s1}\}]^{1/\epsilon_M}}{\mathbb{E}[B_{sj} exp\{V_{sj}\}]^{1/\epsilon_M}} = \frac{L_{s1t}}{L_{sjt}}$$

which can be reduced as:

$$L_{ujt} = f(V_{ujt}^{\frac{1}{\epsilon_M}}) \cdot Constant$$
$$L_{sjt} = f(V_{sjt}^{\frac{1}{\epsilon_M}}) \cdot Constant$$

Now suppose there are two different solutions for location j, (L_{ujt}, L_{sjt}) and (L^*_{ujt}, L^*_{sjt}), each satisfying the equilibrium conditions above. For a given population in location one, without loss of generality, assume $L^*_{ujt} > L_{ujt}$, implying $V^*_{ujt} > V_{ujt}$. Since both V_{ujt} and V_{sjt} depend on and increase with the local wage-housing-price ratio $\frac{w}{p^h}$, it follows that $\frac{w^*}{(p^{h*})} > \frac{w}{p^h}$, leading to $V^*_{sjt} > V_{sjt}$ and so $L^*_{sjt} > L_{sjt}$. This suggests a scenario where both the total population and utility are higher in the first solution than in the second. However, this contradicts the model's premise that a monotonic increase in the population of both types should lead to a decrease in the utility levels. Intuitively, limited land area in a specific city is a natural congestion forces, while no aggregation force is assumed in this model, so the spatial equilibrium is uniquely determined across locations.

Given this result, it becomes evident that the total population at any location j–and consequently, the entire economy's population–is increasing with the population at the base location. Similarly, the skill ratio, defined as the proportion of skilled workers, at any location j–and thereby the skill ratio of the entire economy–is increasing in the skill of the base location. Therefore, we offer a proof sketch for the uniqueness of the steady state in a single-location model (the national level). This proof can be readily extended to a multi-location model based on this cross-sectional rule.

Uniqueness of Steady State in the Base Location When consider the steady state in a "One Location Model," we can shift the focus from the populations of two types, (L_u, L_s), to the total population L and the skill ratio s. A steady state is then defined as a set of variables (L, s) that satisfy the following conditions:

$$\frac{L'(L,s)}{L} = 1 \tag{A1}$$

$$s'(L,s) = s \tag{A2}$$

where L' and s' represent the total population and skill ratio for the next period, respectively. Notably, there are a few properties of the two functions:

1) $\frac{L'(L,s)}{L}$, representing the aggregate fertility rate, decreases with L. This is due to the fact that both output per capita and housing per capita will both decline with more population (congestion force), leading to a decrease in fertility rate.

2) $\frac{L'(L,s)}{L}$ decreases with s, as skilled workers have a higher probability of raising skilled children and so a lower birth rate ("Quantity-Quality" Tradeoff).

3) $s'(L,s)$ increases with s; even though, the derivative $\frac{\partial s'}{\partial s} < 1$, and the range $|s'(L,1) - s'(L,0)| < 1$, which means that even when populations are entirely skilled or unskilled individuals, the offspring will not be exclusively of one type.

4) $s'(L,s)$ increases with L. As the total population grows, the housing price to wage ratio increases, which elevates the cost of child-rearing and incentivizes parents to prioritize the quality of children over quantity.

After establishing these properties, let's begin with Equation A2. For any given total population L, there exists a skill ratio s^* such that:

$$s^* = s'(L, s^*)$$

This relationship defines s^* as an implicit function of L, denoted $\mathcal{S}(L)$. We then reformulate the fertility rate from Equation A1 as follows:

$$\frac{L'(L,s)}{L} = g(L,s)$$

By substituting $\mathcal{S}(L)$ for s, this equation can be simplified to a function of L alone:

$$f(L) = g(L, \mathcal{S}(L))$$

Taking the derivative:

$$f'(L) = \underset{(-)}{\frac{\partial g}{\partial L}} + \underset{(-)}{\frac{\partial g}{\partial s}} \underset{(+)}{\frac{\partial \mathcal{S}}{\partial L}} < 0$$

Therefore, it is evident that there is only one unique solution for the equation:

$$f(L) = 1$$

which corresponds to Equation A1. Thus, we finish the proof that there is only one solution satisfying both Equation A1 and Equation A2, establishing that the steady state in the national level is unique. Added to the first proof above that the cross-sectional equilibrium is also unique, it becomes clear that the steady state for the whole system is uniquely determined.

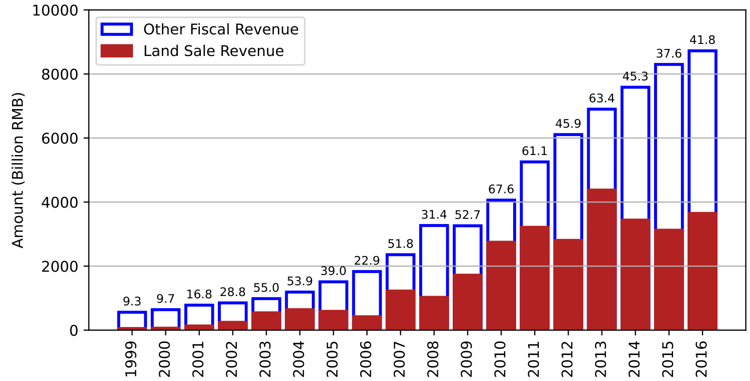
Appendix VI. Extra Tables and Figures

Table A1—The Share of High School Attainment for each Cohort from 1980-2010

Year	Share(%)	Year	Share(%)	Year	Share(%)
1981	18.8	1991	27.2	2001	37.2
1982	18	1992	28.6	2002	39.3
1983	19.9	1993	29.4	2003	42.5
1984	21.5	1994	30.3	2004	45.3
1985	21.8	1995	31.8	2005	48.8
1986	22.3	1996	31.7	2006	53.4
1987	23.2	1997	33.4	2007	59.4
1988	24.1	1998	34.1	2008	60.8
1989	24.4	1999	34.8	2009	56
1990	26.1	2000	35.3	2010	36.3

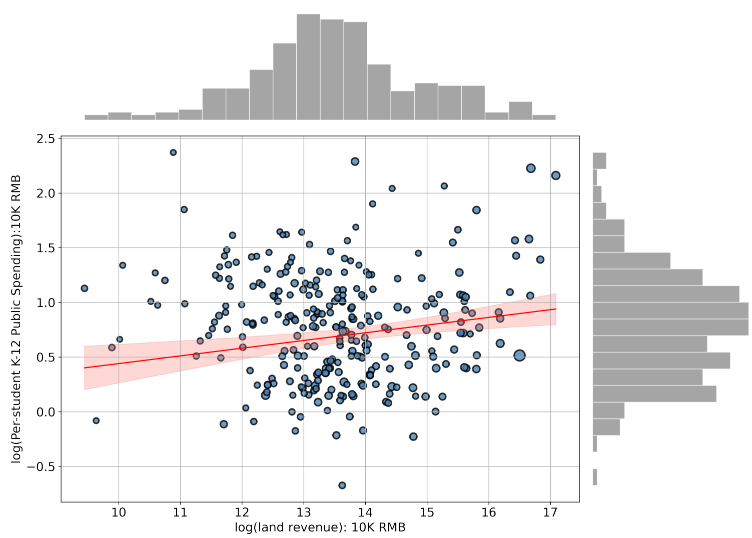
Notes. A cohort includes all individuals born within a one-year span, from September to August. Cohorts are identified by the year in which the majority of the members turn 15 and decide whether to attend high school. For instance, the 2008 cohort consists of individuals who turn 15 in 2008. A city's high school education rate is defined as the ratio of individuals who received at least a high school education to the total population in the same cohort.

FIGURE A1. SOURCES OF LOCAL GOVERNMENT REVENUES AND LAND SLAES



Notes: The fiscal revenue data comes from CCER Economics and Finance Database. Land revenue data comes from China Land and Resources Statistic Yearbooks. Each bin stands for the local government's total fiscal revenue (measured in 100 million RMB), and the light and dark part stands for fiscal revenue coming from land sales and other sources, respectively. The numbers on top of the bin denote the proportion of fiscal revenue from land sales.

FIGURE A2. LAND SALE REVENUE AND PUBLIC EDUCATION EXPENDITURE, 2010



Notes: Data on public education expenditure and the K-12 student population are sourced from the China City Statistical Yearbook (2010). Land revenue data for each city comes from the China Land and Resources Statistical Yearbook (2010).