8-23-2024

ESSAYS ON INTERNAL MIGRATION, EDUCATION, AND TRADE LIBERALIZATION

Jingxuan Du
Syracuse University

Abstract

This dissertation explores the intersection of urban economics, education, and international trade impacts in developing countries, comprising two chapters.

Chapter 1 examines how internal migration affects structural transformation and intergenerational educational mobility in China using a dynamic quantitative spatial equilibrium framework. Recent decades of massive rural-urban migration have profoundly impacted China's economy, with migrants facing dilemmas about relocating with their children—a decision that affects intergenerational educational attainment. To evaluate the welfare effects of internal migration and understand the underlying mechanisms, I develop an overlapping generations spatial equilibrium model where migrants confront children's placement choices. Model estimation reveals that allowing all parents to migrate with their children induces structural change and increases welfare, primarily by improving educational mobility. Counterfactual analyses demonstrate that reducing migration costs narrows the overall welfare gap between skill groups, stimulates structural transformation, and significantly improves educational mobility, albeit at the cost of increased spatial inequality. The findings support relaxing migration control policies while improving rural education quality to mitigate growing inequality.

Chapter 2 investigates the impact of trade liberalization on intergenerational education mobility, focusing on China's WTO accession. The study finds that export tariff reductions have a more significant negative impact on educational outcomes for children from low-educated families compared to those from high-educated families, thus reducing intergenerational education mobility. Estimations of intergenerational education elasticity corroborate this finding. The study argues that the opportunity cost of education alone cannot fully explain these results and identifies another crucial mechanism: parents reduce time and effort invested in their children's education to pursue new job opportunities and higher incomes, negatively affecting early childhood development.

ESSAYS ON INTERNAL MIGRATION, EDUCATION, AND TRADE LIBERALIZATION

by

Jingxuan Du

B.A., Beihang University, 2017

M.A., Renmin University of China, 2019

Dissertation

Submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in *Economics*.

Syracuse University

August 2024

Acknowledgements

I want to express my deepest gratitude to my advisors, Devashish Mitra and Alexander D. Rothenberg, for their unwavering support, insightful suggestions, and selfless help throughout my PhD journey. Their expert guidance, consistent encouragement, and immeasurable devotion helped me build confidence and navigate difficult times. The time I spent with them is a precious treasure that I will carry with me throughout my lifetime.

I would like to express my appreciation to Ryan Monarch, Thomas Pearson, and Zibin Huang for their detailed advice and valuable feedback on my research and professional development, especially during the job market cycle. Additional thanks go to all the professors who taught my major courses and with whom I worked as a teaching assistant, the staff at the Moynihan Institute of Global Affairs, and those who organized the Trade, Development, and Political Economy (TDPE) Group.

I also wish to thank my classmates and friends at Syracuse: Zeyuan (Victor) Xiong, Jooyoung Kim, Kyuhan Choi, Zhuoran Shang, Brian Green, Zhe He, Jorge Valdebenito, Fan Yang, and Wenzhen Lin - you made my journey colorful and enjoyable. Specifically, I want to express my sincere gratitude to Yinhan Zhang, who gave me priceless friendship, steadfast support, and shared interesting life experiences with me. I will never forget the days we discussed all kinds of issues, had meals together, and went on trips. I wish our friendship will last forever.

Finally, I would like to dedicate this dissertation to my family and friends in China. My parents' unconditional and thoughtful devotion has made me who I am today - you

shouldered all the pressure and burden, creating a safe and pleasant shelter for me throughout my lifetime, encouraging me to move forward and pursue my dreams. My grandparents have instilled in me their endless love, and my friends from childhood have accompanied me through life's journey. I'm lucky to have all of you by my side.

Contents

List of Figures

List of Tables

Chapter 1

Internal Migration, Eduational Mobility and Structural Transformation

1.1 Introduction

Massive rural-to-urban migration has been a significant driving force behind China's rapid structural transformation in recent decades. This migration has been driven by better job prospects, higher wages, and improved educational opportunities in urban areas. However, high living costs and restrictive access to local resources influence migrants' decisions regarding where to relocate and whether to move with their children. While existing literature primarily focuses on the impacts of migration barriers on productivity and labor allocation (Tombe and Zhu, 2019; Fan, 2019), few studies emphasized the intergenerational consequences of these barriers. Since childhood location is a critical determinant of children's educational and economic outcomes (Eckert and Kleineberg, 2021; Chetty and Hendren, 2018), these impacts also play a crucial role in a nation's long-term human capital accumulation, economic growth, and the spatial distribution of economic activities.

This paper investigates how different migration barriers influence migrants' decisions regarding sector, location, and whether to move with children, and how these decisions impact structural transformation and intergenerational educational mobility across regions. Addressing these questions is challenging because migration barriers encompass both tangible relocation costs, such as physical distance, and policy-induced hurdles, like the hukou system, which imposes constraints on migrants' access to housing ownership, local insurance, and educational opportunities for their children. Additionally, migration decisions are influenced by economic factors and the perceived value of educational opportunities for children, complicating causal identification. In a general equilibrium framework, migration flows affect local labor markets, consumption prices, and the allocation of educational resources among diverse demographic groups.

To address these concerns, this paper introduces a dynastic quantitative spatial equilibrium model with overlapping generations that formalizes education and family migration choice. I proceed in four steps. First, I describe the spatial distribution of migrant families and examine the relationship between children's migration status and their educational attainment. Using a unique dataset in China, I find that compared to children with local hukou, children from skilled families without local hukou have a 0.22 standard deviation lower test scores.[1] On average, left behind children from unskilled families has a 0.092 standard deviation lower test score. These results suggest either moving with parents or being left behind imposes negative impacts on children's human capital accumulation, compared with their native counterparts (Huang, 2022).

Second, I develop an overlapping generations spatial equilibrium model to capture the forces shaping spatial migration patterns, educational attainment, and structural transformation. At the end of the first period, teenagers aged 16 decide whether to attend high school based on local education quality, the returns to education, and the human capital they accumulated during childhood. After making their educational choice, they enter adulthood

[1]Test scores are measured on the basis of standardized cognitive test to all students in this specific education panel survey, which will be detailed later.

and have children. Their choices of adulthood location and sector reflect their idiosyncratic preferences, wages, amenities, moving costs, and the future utility each destination offers to their children. They also decide whether to migrate with their children if they move. In general equilibrium, educational, sectoral, and residential decisions jointly determine the supply of educated workers in each location. Local production technologies, which vary in productivity and skill intensity, shape the local demand for workers of different skill groups.

Workers face costs associated with migration, sector transitions, and child placement, which vary by education level and location. To capture the wedge created by hukou system, I assume workers with local hukou status enjoy land ownership, superior amenities, and higher educational quality compared to non-hukou holders. A pivotal mechanism in the model is that the heterogeneous migration costs on migrants with different child-placement decisions influence their location and sector choices. For instance, cities with prohibitively high child-placement costs may deter migrants from moving with their children, pushing them to alternative destinations. This dynastic sorting process among skill groups and their offspring contributes to distinct migration patterns over a long period.

The model incorporates a standard production and trade framework as outlined in Eaton and Kortum (2002), where agricultural and industrial goods are tradable subject to iceberg costs, while service goods remain non-tradable. Labor market clearing conditions determine local wages and skill premia within each spatial unit, reflecting variations in education quality, land rents, amenities, and productivity. By introducing non-homothetic preferences, the model integrates demand-side drivers of structural change, as emphasized in the previous literature (Takeda, 2022).

Then I develop key intuitions using a simplified two-location model. First, increasing the rural-urban migration cost and the hukou threshold increases the welfare gap between skill groups and reduces educational mobility at the national level. Second, the introduction of migrant children's costs reduces the overall welfare and educational mobility, especially affecting unskilled workers and migrants.

In the third step of analysis, I estimate the migration, sector labor supply, and education elasticities using rich micro and macro data from China's population census, statistical yearbook and several representative micro survey datasets.[2] Exploiting the structure of this model, I estimate the migration elasticity from a gravity equation with instrumental variable strategy. The elasticity of migration is 0.62 and 0.74 for skilled and unskilled workers, respectively, comparable to the estimates of Tombe and Zhu (2019).

Three key parameters that determine the total migration costs in my model include: (1) the probabilities of obtaining local hukou, reflecting the difficulty of accessing local amenities for migrants; (2) calibrated migration costs net of child-related expenses; and (3) child-placement costs. I calculate the probabilities of obtaining local hukou for different skill groups from census data. Then I calibrate the net migration costs using a nested nonlinear least squares method, similar to Fan (2019). I specify a migration cost equation including time-invariant cultural and geographic distance as well as time-variant origin-destination characteristics, choose parameters of the migration costs function, and then find the amenities to match the local aggregate labor data in the inner loop. With these inverted amenities, I can pin down the coefficients of migration costs by minimizing the distance between the data and predicted migration flow in the outer loop. After that, I employ a nested fixed-point algorithm to invert the model and uncover unobserved fundamentals that match the data exactly, including child-placement costs, education quality, productivities, amenities and native-migrant gaps.[3] The model demonstrates a strong fit for the transition path of structural transformation and urbanization at the national level, and the relationship between the distribution of some untargeted moments and data are significantly positive.

Armed with the estimated parameters and calibrated costs, I begin by quantifying the impact of the child placement decision by mandating that all parents move with their children. The results indicate that educational mobility for migrant children doubles, leading

[2]These datasets include Chinese Household Income Project (CHIP), China Education Panel Survey (CEPS) and Urban Household Survey (UHS) at province-area level. Area denotes rural and urban.

[3]The local premium gap include education costs gap and amenities gap, which enter in the model the same way as the probability of obtaining Hukou, so I do not emphasize them.

to a significant increase in the number of young people transitioning to the non-agricultural sector. This shift results in a 31.6% rise in welfare for unskilled workers. Moreover, in the absence of hukou restrictions, educational mobility would quadruple. My findings also reveal that eliminating the educational mobility channel significantly hampers structural transformation, underscoring the importance of human capital transmission across generations facilitated by parents moving with their children.

Finally, I use the model to evaluate the impacts of reducing migration costs on welfare, educational mobility, and structural transformation. I undertake three sets of counterfactuals: (1) removing the hukou threshold in all locations; (2) reducing net migration costs, excluding the time-invariant component, by 30%; and (3) eliminating costs associated with migrant children.

The findings indicate that reducing any of these costs promotes structural change and significantly enhances the educational mobility of children from migrant families. While the welfare of unskilled workers increases more significantly at the national level, locational welfare changes reveal an opposite pattern. This discrepancy between individual and aggregate outcomes arises from the substantial welfare increase in rural areas, where a large share of the labor force is unskilled. Additionally, the reallocation of labor across sectors and regions leads to heightened spatial inequality. Among all kinds of reductions, removing the hukou threshold stands out by significantly increasing educational mobility for urban migrants by 134%. It also substantially improves educational mobility in eastern areas by 25%, in contrast to the comparatively less pronounced impacts observed in other reduction scenarios in this region. This exception suggests that the stringent hukou policy in eastern areas has hindered educational mobility, and removing this restriction could promote growth and welfare.

To examine how the difference in school quality between rural and urban areas interacts with migration cost reduction, I reduce educational costs in rural areas to the same levels as those in urban areas within each province and conduct the same set of counterfactuals.

In this scenario, the welfare gap between skilled and unskilled workers becomes smaller, and educational mobility is significantly higher in rural areas. However, the non-agricultural employment share and average welfare are lower than in the baseline case. Therefore, due to diminishing marginal returns, the impacts of lower migration costs on reducing welfare inequality and improving the educational mobility of children from migrant families at the national level become less significant. Nevertheless, structural transformation and the urbanization rate increase more substantially.

This research speaks to a broad literature on the spatial distribution of structural change with non-homothetic preferences (Fan, Peters and Zilibotti, 2023; Chen et al., 2022; Herrendorf and Schoellman, 2018), and the research that emphasizes the role of human capital transmission in the structural transformation process (Caselli and Coleman II, 2001; Porzio, Rossi and Santangelo, 2022; Valencia Caicedo, 2018). An emerging strand of research has also considered labor frictions across space within a nation (Eckert and Peters, 2022; Takeda, 2022); Hao et al. (2020) finds that migration barriers are central to China's structural transformation and regional income convergence. This work contributes to the existing literature by considering labor mobility and educational transmission within a unified framework. It characterizes the impact of migration on structural transformation through educational transmission, while allowing for the feedback effects between these elements.[4]

It also links to research on intergenerational mobility, education and internal migration (Chetty and Hendren, 2018; Chetty, Hendren and Katz, 2016; Caucutt and Lochner, 2020). Several studies examine the role of family migration in shaping economic geography (Imbert et al., 2023) and structural transformation (Cao et al., 2023). My quantitative model builds on the framework introduced by Eckert and Kleineberg (2021), who embed a spatial equilibrium model in an OLG structure that links children's educational outcomes to their childhood location and studies the effects of school funding equalization on educational out-

[4]Instead of assuming that rural-urban migration is identical to structural change, as most of the existing literature does, I assume that both rural and urban areas have three distinct sectors, and the variation in sector composition is due to different sector-switching costs, consistent with the fact that over 30% of rural workers were employed in non-agricultural sectors in 2005.

comes and social mobility. In contrast to their work, which uses a function of school funding per pupil and a local exogenous component as a proxy for educational quality, I specify children's human capital production as a function of parental investment and migration status, where the local exogenous component depends on the child's location decision instead of the parents' destination. This type of model specification endogenizes educational choice and thus promotes richer insight into the effects of migration policy reforms, which is of particular interest in China.

Last but not least, this research contributes to a growing literature also uses quantitative models to estimate the impact of lowering migration barriers in China (Wu and You, 2023; Tombe and Zhu, 2019; Hao et al., 2020; Hsu and Ma, 2021). However, few studies consider the education choice in an integrated framework,although recent empirical studies have shown that migration barriers have increased the proportion of left-behind children and negatively affected their educational outcomes (Liao et al., 2020; Démurger, 2015; Yuanyuan Chen, 2023; Shu Xu, 2023). Notable exceptions include Sieg, Yoon and Zhang (2023), who quantify the positive impact of migration policy reforms on the educational attainment of migrant children born in rural areas, and Huang (2022), who develops a spatial equilibrium model accounting for peer effects and find that relaxing migration constraints can increase migration and national human capital. My research delves into the relationship between migration and education transmission using a dynamic framework that features structural transformation, and explores how inequality in the distribution of educational resources interacts with migration cost reductions—a second-order effect that few researchers have explored.

The rest of this paper is organized as follows. Section 2 presents background information on structural transformation and migration policy in China, section 3 presents the empirical specification and results, section 4 presents the model I develop, and section 5 explains how I estimate certain parameters of the model and calibrate others. Section 6 presents the results of quantification and counterfactual exercises and section 7 concludes.

1.2 Background and Motivating Facts

This section contextualizes China's structural transformation and migration patterns, providing pertinent institutional backgrounds and summary statistics. It then empirically investigates the influence of migration status on children's educational outcomes using micro-survey data.

1.2.1 Structural Transformation and Migration Pattern in China

China has undergone significant structural transformation in recent decades. Figure 1.1 illustrates this trend, showing the sharp decline in both GDP value added (VA) share and employment share in the agricultural sector in Panel (A) and Panel (B), respectively. Conversely, the service sector has experienced steady growth. Its share in GDP value added has increased consistently since the mid-1980s, surpassing that of industry in 2012 and now comprising over half of the total VA. Additionally, the service sector now accounts for the largest share of total employment.

This structural shift aligns with a massive internal migration in China. Census data indicates a substantial growth in migration from 7 million in 1982 to 376 million in 2020, and its share increases from 0.7% to 26.6% of the total population. Rural-to-urban migration has predominated over the past two decades, rising from 57% to 66.2% of total migration. However, the gap between permanent and registered urban residents continues to widen, increasing from 10.22% to 18.5%, reflecting the lagged population urbanization caused by restrictive hukou system.

Hukou System and Migration Mode. The hukou (household registration) system assigns each citizen an urban registration card, typically in their birth county. This system has significantly impacted internal migration and access to public services since its birth in 1950s. Migrants without local urban hukou face limited access to education, healthcare, and housing, as well as labor market discrimination. After 1978, the system was gradually relaxed to allow individuals to move to other places under certain circumstances. Since 2000, the reform of hukou system has been greatly promoted in small and medium-sized cities. After 2013, the reform continued to increase in strength and scope, differed by city size. However, migrant workers still face difficulties in obtaining local urban hukou in some cities now. According to the latest census in 2020, although 63.9% of the population lives in urban areas, only 45.4% have urban hukou.

Massive internal migration in China has led to a significant increase in migrant children. Figure 1.4 shows that the size of migrant children grew from 50 to 130 million during the past two decades, now comprising over 40% of China's child population. While most were left-behind children until 2015, migrant children accounted for 54.5% of children from migrant families by 2020.

Since the late 1980s, migrant parents have faced challenges enrolling their children in urban schools. They often paid "education endorsement fees" until this practice was banned in 2004. However, enrollment difficulties persist, especially in large cities(Dong and Goodburn, 2020). Many migrant families, particularly those socioeconomically disadvantaged, choose to enroll their children in migrant-organized schools, which often have poor infrastructure and less qualified teachers(Liang et al., 2020; Chen and Feng, 2019).

Recognizing this issue, the Chinese government has implemented policies since 2001 to address enrollment problems in compulsory education. Figure 1.3 shows the proportion of children living with migrant parents increased from 34% in 2010 to 52.6% in 2020, with those attending public schools rising from 26.8% to 42%. According to 2012 National Migrant Population Dynamic Monitoring Survey, around 80% of migrant children are now enrolled in public school, with substantial spatial variation: the proportion in central areas reaches 92% contrast to 75% in eastern areas. In metropolis like Beijing and Shanghai, the limitations on enrollment is still extremely tight. Recent research on the enrollment thresholds of compulsory education (Shu Xu, 2023) and high school (Yuanyuan Chen, 2023) in different prefectures has found that increasing restrictions on school enrollment increase the probability that children in rural areas will be left behind, and the negative effects are concentrated mainly on unskilled families.

1.2.2 Parental Migration and Children's Education Performance

The Hukou system in China has resulted in a significant number of left-behind and migrant children, adversely affecting their educational performance and overall health (Liao et al., 2020). These early-life challenges often translate into lower educational attainment in their future. In this part, I examine the impacts of children's migration status on education attainment using the data of China Education Panel Survey (CEPS), which is a nationally representative panel dataset with two waves.

Data and Specification. In 2013, the survey interviewed 19,487 students from 112 middle schools across the country, with 10,279 from grade seven (class of 2016) and 9,208 from grade nine (class of 2014). In 2014, they followed up with students from the class of 2016, who were then in eighth grade. The class of 2014 was not included in the second wave since they had already graduated. The survey gathered information from students, their parents, teachers, and school principals, including whether the students hold local hukou and whether they live with their parents. Following Huang (2022), I define migrant students as students without local hukou and left-behind students as those living with only one or no parent.[5] To avoid biases caused by arranging students by academic performance, I select schools that (1) randomly assign new students in their first year and (2) do not reassign students in the second year. I also cross-check the data using responses from both the principal and head teachers.

After cleaning up the data, I get 9748 observations across two waves with 6733 identical students. Among them, 12.6% are migrants and 17.4% are left-behind children, adjusted by sampling weight. Table 1.1 presents the summary statistics and results of group comparisons by migration status using two-sample t-tests. It shows that left-behind children

[5] I do not count students whose parents are divorced or have died as left-behind. This information is only available for the class of 2016; therefore, I only use the class of 2016 across two waves.

have significantly lower standardized scores and expectations of attaining at least a high school education. They tend to be predominantly female, possess an agricultural hukou, have siblings, live with married parents, demonstrate proficiency in local dialects, originate from unskilled households, and are typically placed in classes with fewer migrant classmates and more left-behind peers. On the other hand, migrant children tend to be less proficient in the local dialect and are more likely to be in classes with fewer left-behind peers but more migrant classmates.

Many researchers have studied the human capital formation of children, and some estimate the production function of human capital as a outcome of parental investment and family characteristics (Attanasio et al., 2020; Heckman, 1976). I use the standardized cognitive score provided by CEPS and estimate the human capital production function based on the score[6]. Since CEPS does not track students after graduation, I define expected high school attainment as one if the highest education expectation from both students and their parents is at least high school[7]. For student i in class j, school s, and interviewed in year t, I run the following OLS specification for each family group g separately :

$$y_{gjst}(i) = \theta^g log(education\_invest_i) + \alpha_1^g Left\_behind_i + \alpha_2^g Migrant_i + \theta_x^g log(SchoolExp)_{st} \tag{1.1}$$

$$+ \theta_q^g log(SchoolSize)_{st} + \Gamma_g X_{ijst} + FE_{XT} + \epsilon(i)$$

where $y_{gjst}(i)$ denotes the educational outcome variables for student i, $education\_invest_i$ denotes the parental education investment to children,[8] $Left\_behind$ and $Migrant$ are dummies that indicate children's migration status, $SchoolExp$ denotes the school's expenditure

[6]The CEPS gave a standardized cognitive test to all students in both waves. This test comprises sections on language and reading, geometry and spatial reasoning, and computation and logic. It is designed to assess logical reasoning and problem-solving capabilities.

[7]CEPS does not track the students after they graduate, so I define the expected high school attainment as one if the highest education expectation from students and their are both equal or above formal high school.

[8]There are half of zero observations of this variable, so I take the $\log(i+1)$.

on students per capita and $SchoolSize$ is the number of students at this school. In the baseline, the FE_{XT} controls for class-by-year fixed effects, and X_{ijst} controls for a set of personal level variables including student age, agricultural hukou dummy, gender, whether he or she is the only child, dialect proficiency, parents' marriage status in the baseline specification. θ_i^g, α_1^g and α_2^g are three key parameters of interest. To reveal the impact the school expenditure and scale effects, I employ an alternative specification that solely incorporates county-by-year fixed effects. Additionally, this specification encompasses controls at both the class and school levels, which encompass information about the head teacher, the proportion of migrant and left-behind peers in the class, the school's ranking, as well as the native ratio.[9]

Results. The mean and standard deviation of the cognitive test scores in my sample are 0.14 and 0.87, respectively. Baseline results in Column (1) and (2) of Table 1.2 indicate that a 10% increase in educational investment boosts test scores across all students by 0.22 points, approximately 25% of the standard deviation. On average, migrant students from skilled families score 0.188 points lower than their non-migrant counterparts from skilled families. In contrast, there is no significant difference observed among students from unskilled families. However, left-behind students from unskilled families exhibit significantly lower test scores, approximately 0.08 points less than their peers, with no significant disparity noted among students from skilled families.

Column (3) and (4) of this table reveal that students from skilled families are more likely to benefit from both school expenditure and scale effects. Columns (5) and (6) present the results of expected high school attainment using a logit regression. A 10% increase in educational investment raises the probability of obtaining at least a high school diploma by 65% for those from unskilled families. Left-behind children are 27% less likely to attend high school compared to their peers from unskilled families. While migrant children show a higher probability of attending high school, the coefficients for both groups are statistically

[9] Huang (2022) emphasizes the role of peer effects in their regression, but my focus is on the migration status of student himself, so I only report the results of peer effects on appendix.

insignificant.

Although migrant children may perform worse than native children, their situation may still represent an improvement over a counterfactual in which they do not move with their parents. Due to data limitations, it is not possible to establish a causal relationship here. To address endogeneity concerns related to migration and left-behind status, I employ the sensitivity analysis suggested by Oster (2019). The results in table 1.3 indicate that unobservable factors would have to exert at least 3.8 times the influence of observable factors to negate the negative coefficients observed for migrants in column (1) and at least 1.3 times for left-behind children in column (2).

These findings suggest that parental migration status adversely affects students' educational outcomes. Left-behind children from unskilled families are particularly impacted by parental separation, while migrant children face challenges related to unfamiliar environments and discriminatory policies. It is crucial to recognize that the treatment effects are difficult to estimate due to spillover effects in general equilibrium. To account for all relevant mechanisms and general equilibrium effects, I adopt a dynastic quantitative spatial equilibrium framework, estimate the parameters using the model structure, and implement counterfactual analysis.

1.3 Model

This section introduces a dynastic spatial general equilibrium model designed to evaluate internal migration, improve upon reduced-form analyses by connecting data with policies more effectively, and examine counterfactual policies. The model incorporates standard ingredients, with the economy evolving in discrete time, indexed by $t \geq 0$, and consisting of provinces with rural and urban areas, indexed by $n \in \{1, 2, ...N\}$. In each period, the economy is inhabited by a mass of children and adults. Firms operate under perfect competition with province-sector specific productivities, agricultural and industrial goods are tradable within country and abroad whereas service goods are non-tradable.

1.3.1 Workers

Timeline and Decisions. I begin by outlining the decision process of an individual i living across two periods: childhood and adulthood within overlapping generations. Figure 1.5 illustrates the life cycle of these two generations, following the framework proposed by Allen and Donaldson (2020). In period $T = 1$, individual i is born and raised in location o, which is chosen by their parents. By the $T = 1$, individual i experiences an educational taste shock ϵ_e, makes an education choice $g \in \{L, H\}$, and enters adulthood in $T = 2$.

During $T = 2$, individual i anticipates economic conditions and the probabilities of obtaining local hukou $\theta_d(g)$ across potential destinations. They receive a location preference shock ϵ_d and decide on a location d within the country to reside. The possession of a local hukou q determines their access to local resources. Subsequently, they encounter a sector productivity shock z_j and select an industry from agriculture, industry, or service, denoted as $\{F, G, S\}$. After making location and sector choices, they raise a child and decide whether to move with their child to d or leave them behind in o[10], considering both their own benefits of living in a place and the expected benefits for future generations of their family.

Preference. Worker preferences within each period t are modeled as the Price-Independent Generalized-Linear (PIGL) preference with the following indirect utility function:

$$u^g_{dj}(q) = \frac{1}{\epsilon}\left[\frac{e^g_{dj}(q)}{\mathbb{P}_{dj}}\right]^{\epsilon} - \sum_{k\in J}\gamma_k \ln P_{dk} \tag{1.2}$$

for individual of skill g, hukou status q, working in location d and sector j, with nominal income $e^g_{dj}(q)$. He consumes goods from agriculture (F), industrial (G), service (S) sectors and spends a fixed share of expenditure on housing, so the price index $\mathbb{P}_{dj} = (P^{\omega_F}_{dF} P^{\omega_G}_{dG} P^{\omega_S}_{dS})^{\alpha}(r_{dj})^{1-\alpha}$, where $P_{dk}, k \in \{F, G, S\}$ is the final price for each sector k, ω_k

[10] I abstract from fertility decisions and assume everyone has one child.

approximate the expenditure share on each sector, r_{dj} is the location-sector specific price of land, and α is the expenditure share on non-housing goods. The parameter γ_k governs the sensitivity of expenditure shares to changes in relative prices whose sign determines whether the good is a luxury ($\gamma_k < 0$). ϵ governs the sensitivity of expenditure shares to changes in income. Compared with homothetic preferences, this type of utility can capture both the relative price effect and the income effect that drive structural change from the demand side, consistent with the fact that the expenditure share on agricultural goods decreases as people's income levels rise.

Dynamic Decision Problem. Workers with skill level g and childhood location o chooses their adulthood living location d and working sector j by solving the following maximization problem:

$$V(o,g) = E_{\epsilon_d,\eta_j} \max_{d,j} \{\bar{u}^g_{dj}(q) - \mathcal{C}^g_{od} - m^g_d(j) + \tilde{B}^g_d(q) + \nu \mathcal{O}_{od}(g) + \epsilon_d + z_j\} \tag{1.3}$$

where $\bar{u}^g_{dj}(q) = \theta_d(g)u^g_{dj}(1) + (1-\theta_d(g))u^g_{dj}(0)$ is the expected flow utility per-period for workers of migration status q, and ν is the altruistic parameter. $\tilde{B}^g_d(q) = [\theta_d(g)B^g_d(1) + (1 - \theta_d(g))B^g_d(0)]L^{\xi}_d$ is the expected amenities for individual of g who live in d with migration status q, where $B^g_d(0) < B^g_d(1)$ captures the wedge between natives and migrants and ξ captures the negative congestion effects. $\mathcal{C}^g_{od}$ is the group-origin-destination specific migration costs from o to d of group g, and $m^g_d(j)$ is the group-location specific sector switching costs from agriculture to $j \in \{G, S\}$. $\mathcal{O}_{od}(g)$ is the expected utility for children from migrant family with skill g, moving from o to d, which is determined by parent's child-placement choice:[11]

$$\mathcal{O}_{od}(g) = E_{\varepsilon} \max_{c \in \{LB, MIG\}} \{O(d,g,q) - t^g(d|MIG) + \varepsilon_d, O(o,g,q) - t^g(o|LB) + \varepsilon_o\} \tag{1.4}$$

where choices set LB, MIG denotes leaving children behind and moving with children, and

[11] Migration status q is omitted here as od pins down q.

for local residents $\mathcal{O}_{oo}(g) = O(o, g, Stayers)$. $t^g(d|MIG), t^g(o|LB)$ denote the additional migration costs related to moving with children to d and leaving them behind in o, respectively. The expectation is taken over parent's idiosyncratic shock regarding child-placement choice ε. $O(d, g, q)$ is the expected utility of child grown up in d from family skill g and migration status q. I call this term as "child opportunity value", similar to Eckert and Kleineberg (2021), which is given by:

$$O(d, g, q) = E_{\epsilon_e} \max_{g' \in \{H,L\}} \{V(d, g') - \mathbb{I}_H \tilde{Z}_d^g(q) + \epsilon_e\} \tag{1.5}$$

$V(d, g')$ is the expected continuation value that location d offers to the young adults with skill level g', $\tilde{Z}_d^g(q) = \theta_d(g) Z_d^g(1) + (1 - \theta_g(d)) Z_d^g(0)$ is the expected education cost her family needs to pay if she chooses to go to high school, where $Z_d^g(1) < Z_d^g(0)$ captures the additional costs paid by migrants. This cost increases in a location-specific cost, decreases in parental human capital investment and government expenditure. The expectation is taken over the child's education taste shock ϵ_e.

This dynastic structure emphasizes the key mechanism in this model − parental child-placement decision, local government's expenditure on public resources, and policy-induced wedge between natives and migrants, captured by $B_d^g(q)$ and $Z_d^g(q)$, together determine the education attainment for younger generation. Intuitively, if the wedge between migrants and natives reduces or the probability of obtaining local hukou increases, parents are more likely to move with children, and thus enhancing the intergenerational mobility.

1.3.2 Production

Producers in each location d and sector j use composite labor E_{dj} and fixed-supplied land $\bar{H}_{dj}$ to produce output y_{dj} of the variety supplied by that location in that sector[12]. Production

[12] Composite labor $E_{dj} = [(\lambda_{dj})^{\frac{1}{\rho}} (L_{dj}^H)^{\frac{\rho-1}{\rho}} + (1 - \lambda_{dj})^{\frac{1}{\rho}} (L_{dj}^L)^{\frac{\rho-1}{\rho}}]^{\frac{\rho}{\rho-1}}$ where ρ is the elasticity of substitution of labor and λ_{dj} is region-sector-labor market type specific intensity of skilled labor, and composite wage is $W_{dj} = [\lambda_{dj}(w_{dj}^H)^{1-\rho} + (1 - \lambda_{dj})(w_{dj}^L)^{1-\rho}]^{\frac{1}{1-\rho}}$.

is assumed to occur under perfect competition and subject to the following constant returns to scale technology:

$$y_{dj} = z_{dj} E_{dj}^{\beta_l^j} \bar{H}_{dj}^{\beta_h^j} \quad , c_{dj} \propto \frac{(W_{dj})^{\beta_l^j} (r_{dj})^{\beta_h^j}}{z_{dj}}, \quad j \in \{A, I, S\}$$

where c_{dj} gives the unit production cost, W_{dj} and r_{dj} are the composite wage and land price, respectively. For simplicity, I assume the share of skilled-labor and unskilled-labor in total labor cost $W_{dj}E_{dj}$ is η_{dj}^L and $1 - \eta_{dj}^L$[13]. Productivity $z_{dj} = \bar{A}_d^j (l_d^j)^{\gamma_T^j}$, where $\bar{A}_d^j$ is the region-sector specific fundamental productivity and γ_T^j is the agglomeration parameter differed by sector. $l_n^j = E_{dj}/H_{dj}$ is the density of composite workers.

We assume that trade between locations is subject to iceberg variable costs of trade, such that $\tau_{nd}^j \geq 1$ for tradable sector $j \in \{A, I\}$. From profit maximization, the cost to a consumer in location d of sourcing the good produced by location n within sector j equals to its price:

$$p_{nd}^j = \frac{\tau_{nd}^j c_{nj}}{z_{nj}} = \frac{\tau_{nd}^j (W_{nj})^{\beta_l^j} (r_{nj})^{\beta_h^j}}{z_{nj}} \tag{1.6}$$

Suppose that the consumption goods price index for each sector in d depends on the price of the variety sourced from each location n within that sector j that follows a CES function, and therefore the share location d's expenditure within sector j on the goods produced by location n is:

$$P_{dj} = [\sum_{d=1}^{N+1} (p_{nd}^j)^{-\theta}]^{-\frac{1}{\theta}} \quad , \pi_{nd}^j = \frac{p_{nd}^j}{\sum_{d=1}^{N+1} (p_{nd}^j)^{-\theta}} \tag{1.7}$$

where θ is the trade elasticity[14]. For non-tradable service sector, the firms produce one final good using the same inputs, so the price is given by its marginal cost net of productivity. The total revenue in prefecture n and sector k is implied by the gravity equation for tradable

[13]For calibrating the parameters I don't need to know λ_{dj}^H, but I can back them out using $\lambda_{dj}^H = \frac{\eta_{dj}^H}{\eta_{dj}^L} (\frac{w_{dj}^H}{w_{dj}^L})^{\rho-1} / [1 + \frac{\eta_{dj}^H}{\eta_{dj}^L} (\frac{w_{dj}^H}{w_{dj}^L})^{\rho-1}]$. For all counterfactual and steady state calculation, λ_{dj}^H is fixed at this level. It can also be expressed as $\eta_{dj}^H = \lambda_{dj}^H / [(\frac{w_{dj}^H}{w_{dj}^L})^{\rho-1} (1 - \lambda_{dj}^H) + \lambda_{dj}^H]$.

[14]For simplicity, I assume a common elasticity of substitution and trade elasticity across all sectors.

sectors:

$$R_n^k = \sum_{d=1}^{N+1} \pi_{nd}^k X_d^k \quad k \in \{A, I\}; \quad R_n^S = X_n^S \tag{1.8}$$

1.3.3 Income from Land

Similar to Tombe and Zhu (2019), I assume that the land is not tradable and is owned by local residents, which consists with the fact that usually only local residents are able to own house. There is one land market for final consumers and producers within each sector, so their land prices r_{dj} are the same.[15] Workers spend a fixed share of income $1-\alpha$ on housing and producers spend β_h^j on price, therefore the total spending on land of sector j in location d is $(1-\alpha)\bar{e}_{dj}L_{dj} + \beta_h^j R_d^j = (1-\alpha)\bar{e}_{dj}L_{dj} + \frac{\beta_h^j}{\beta_l^j} W_{dj}E_{dj}$, where $\bar{e}_{dj}L_{dj} = \sum_g e_{dj}(g)L_{dj}^g$ is the total income for labor in location d, sector j.

Assuming that the land endowment is inelastic with fixed amount $\bar{H}_{dj}$, the market clearing condition for this factor is: $r_{dj}\bar{H}_{dj} = \beta_h^j R_d^j + (1-\alpha)e_{dj}L_{dj}$. Given workers spend all their income, so the total income of sector j in location d from all sources is the aggregation of income from land, firm revenues, and wages:

$$\bar{e}_{dj}L_{dj} = E_d^j W_d^j + \beta_h^j R_d^j + (1-\alpha)\bar{e}_{dj}L_{dj} = R_d^j + (1-\alpha)\bar{e}_{dj}L_{dj} \tag{1.9}$$

Solving for $\bar{e}_{dj}L_{dj}$ yields $\bar{e}_{dj}L_{dj} = \frac{W_{dj}E_{dj}}{\alpha\beta_h^j}$. Since I denote the share of workers of skill g in wage bill as η_{dj}^g, so the wage bill for group g can be expressed as $w_{dj}^g L_{dj}^g = \eta_{dj}^g \beta_l^j \alpha \bar{e}_{dj}L_{dj}$. The total land income in location d sector j is:

$$r_{dj}\bar{H}_{dj} = \left(\frac{1}{\alpha} + \beta - 1\right)\frac{W_{dj}E_{dj}}{\beta_l^j} \tag{1.10}$$

As only workers with local hukou receive land income, the income of a local worker in location d and sector j of skill g is $e_{dj}^g(q=1) = w_{dj}^g + \frac{r_{dj}\bar{H}_{dj}}{\sum_g L_{dj}^g(q=1)} = w_{dj}^j(1+\delta_{dj})$, where $L_{dj}^g(q=1) = \theta_d(g)\sum_o L_{od,j}^g + L_{dd,j}^g$ is the number of workers with local hukou in d, and the

[15] This relaxation could be relaxed by adding the housing market and land allocation policy.

income of a migrant worker from o is $e^g_{dj}(q=0) = w^g_{dj}$, where local premium δ_{dj} is given by the following:

$$\delta^n_{dj} = \begin{cases} 1 + \frac{\frac{\sum_g w^g_{dj} L^g_{dj}}{\alpha\beta^j_l} - \sum_g w^g_{dj} L^g_{dj}(q)}{\sum_g w^g_{dj} L^g_{dj}(q)} & q = 1 \\ 1 & q = 0 \end{cases}$$

which is one for migrants and larger than one for local workers. Proofs are on the appendix (1.C.2).

1.3.4 Aggregation and Equilibrium

We now solve and aggregate the dynamic education and location choices and use the resulting analytic expressions to define market clearing and the equilibrium of the economy.

Aggregating Individual Decisions. For aggregation purposes, we make the following assumption on the distribution of idiosyncratic preference shocks:

A1. Idiosyncratic shocks over locations, sectors and skill levels $\epsilon_d, z_j, \epsilon_e$ are drawn i.i.d. from a Gumbel distribution with mean zero and dispersion parameters $\sigma^g_d, \eta, \sigma_g$. Preference shock regarding child-placement choice follows a standard Gumbel distribution with dispersion parameter equals one.

Based on this assumption, I can aggregate individuals' choices into the shares of each type that makes a given decision, and derive analytical expressions for the value functions and for the share of agents of each type who make a given discrete choice. Starting from the next generation's skill choice, I solve the problem backwards. The share of the individuals of the next generation study in d with parents' skill g and migration status q becoming workers of skill g' is:

$$Pr(g'|d,g,q) = \frac{\exp(\frac{1}{\sigma_g}V(d,g') - \frac{1}{\sigma_s}\mathbb{I}_H \tilde{Z}^g_d(q))}{\sum_{l'} \exp(\frac{1}{\sigma_g}V(d,l') - \frac{1}{\sigma_g}\mathbb{I}_H \tilde{Z}^g_d(q))} \tag{1.11}$$

And the child opportunity value for a child grown up in d of family skill g and migration status q is:

$$O(d,g,q) = \sigma_g \log\left[\sum_{g'} \exp(\frac{1}{\sigma_g}V(d,g') - \frac{1}{\sigma_g}\mathbb{I}_H \tilde{Z}_d^q(g))\right] \tag{1.12}$$

The share of left-behind children of migrant families from o to d with skill level g is:

$$Pr(Lb|od,g) = \frac{\exp(O(o,g,q) - t^g(o|LB))}{\exp(O(o,g,q) - t^g(o|LB)) + \exp(O(d,g,q) - t^g(d|MIG))} \tag{1.13}$$

The expected utility for children from migrant family with skill g, moving from o to d is given by:

$$\mathcal{O}_{od}(g) = \ln[\exp(O(o,g) - t^g(o|LB)) + \exp(O(d,g) - t^g(d|MIG))] \tag{1.14}$$

Similarly, the share of workers of skill g, migration status q in d working in sector j is:

$$k_d^{gq}(j) = \frac{\exp(\frac{1}{\eta}(u_{dj}^q(g) - m_d^g(j))}{\sum_l \exp(\frac{1}{\eta}(u_{dl}^q(g) - m_d^g(l))} \tag{1.15}$$

And the local expected value in location d for workers of skill g migration status q follows:

$$\bar{U}_d^g(q) = \eta\log\left[\sum_j \exp(\frac{1}{\eta}(u_{dj}^g(q) - m_d^g(j))\right] \tag{1.16}$$

Finally, the share of workers of skill g who move from o to d is:

$$\lambda(d|o,g) = \frac{\exp\left[\frac{1}{\sigma_d^g}(\bar{U}_d^g(q) - \mathcal{C}_{od}^g + \tilde{B}_d^g(q) + \nu\mathcal{O}_{od}(g))\right]}{\sum_l exp\left[\frac{1}{\sigma_l^g}(\bar{U}_l^g(q) - \mathcal{C}_{ol}^g + \tilde{B}_l^g(q) + \nu\mathcal{O}_{ol}(g))\right]} \tag{1.17}$$

And the expected utility of these workers (before knowing any shocks) is:

$$V(o,g) = \sigma_d^g \log\left[\sum_d \exp\left(\frac{1}{\sigma_d^g}(\bar{U}_d^g(q) - \mathcal{C}_{od}^g + \tilde{B}_d^g(q) + \nu\mathcal{O}_{od}(g))\right)\right] \tag{1.18}$$

The Aggregate Law of Motion. Individuals' educational and residential choices determine the distribution of workers across education levels, location and sectors that evolves dynamically over generations. The law of motion (with time subscripts) is given by:

$$L^{g'}_{d'j',t} = \quad k_t(j'|d,g')\sum_d \lambda_t(d'|d,g')\sum_g Pr_{t-1}(g'|d,g) \times A,$$
$$A = [\sum_l Pr_{t-1}(Lb|dl,g)\sum_j L^g_{dl,j,t-1} + \sum_o Pr_{t-1}(Mig|od,g)\sum_j L^g_{od,j,t-1} + \sum_j L^g_{dd,j,t-1}] \tag{1.19}$$

$$where \quad L^g_{dl,j,t-1} = k_{t-1}(j|d,g)\lambda_{t-1}(l|d,g)L^g_{d,t-1}, \quad L^g_{od,j,t-1} = k_{t-1}(j|d,g)\lambda_{t-1}(d|o,g)L^g_{o,t-1}$$

The left hand side (LHS) is the number of generation t's adults of education s' who work in (d',j'), and $L^g_{dj,t-1}$ is the number of parents of skill g who work in (d,j) and $L_{d,t-1}$ is those work in region d. The three terms in brackets denote the number of children raised up in (d,j) with parent with skill g, consist two parts: (1) those who were left behind in d (parents move from d to l) (2) those who migrated with their parents (the pair move from o to d). I also assume children's hukou status changes with parents',and (3) those who didn't move. In the steady state, this distribution is constant across generations, so $L^{g'}_{d'j',t} = L^g_{dj,t}$ holds for all t. But notice that education levels can also change across generations within a given dynasty.

Definition of the Transitional Equilibrium. The exogenous parameters of our model consist of structural parameters and time-varying "regional characteristics" including productivities, amenities and costs. Given path of these exogenous parameters $\{\Omega_t\}_{t=0}^{\infty}$ and an initial distribution of workers $L^g_{dj,0}$ the recursive competitive equilibrium is defined by the paths of:

(a) Family's residential and education choice for each province-sector pair, children status and education level: $\{\lambda_t(d|o,g), k_t(j|o,g), P_t(C|od,j,g), P_t(s'|o,g)\}$;

(b) value functions for each education type and province-sector pair $\{V_t(o,g)\}_{t=0}^{\infty}$;

(c) the distribution of workers across education levels and provincial-sectors: $\{L^g_{dj,t}\}_{t=0}^{\infty}$,

(d) local factor prices $\{w^g_{dj,t}, r^h_{dj,t}\}_{t=0}$ such that:

(i). Residential, children's status and education choices maximize families' utility as derived in equations(1.17)(1.13)(1.11).

(ii). Value functions are consistent with Equations(1.18)(1.4)(1.12).

(iii). The distribution of workers across education levels and locations is consistent with the law of motion in Equation(1.19).

(iv). Wages for each type w^g_{dj} adjust in each location to clear local labor markets, s.t. equation(1.10)(1.9) hold. Good markets clear and firms maximize their profits s.t. equation(1.7)(1.8).

(v). The aggregate expenditure share on agricultural and non-agricultural good of the set of consumers in (d,j) with skill s satisfy Equations(1.8) for all periods.

Existence and Uniqueness of the Equilibrium at the Steady State. A steady state of the economy is an equilibrium in which all location-sector specific fundamentals and endogenous variables are time invariant: $\{A^*_{dj}, \bar{B}^*_d, L^*_{dj}{}^g, w^*_{dj}{}^g, r^*_{dj}, V^*(o,g)\}$.

Proposition 1. One necessary sub-condition for the existence at steady-state is: if $0 < \nu < \sigma^g_d < \sigma_g < 1$ *holds, then the value function has a unique solution which can be computed iteratively applying Pervo Fixed Point Theorem.*

This sub-condition guarantees the existence of the fixed-point of value function, which is a necessary sub-condition for the steady state. This assumption requires that the altruistic parameter, and parameters that govern education and location choices should not be too large to get a convergent value function.

Proposition 2. One sufficient condition for the existence of a unique steady-state equilibrium in terms of the properties of a coefficient matrix A of model parameters $\{\alpha, \nu, \eta, \epsilon, \sigma_g, \sigma^g_z, \eta, \rho, \theta, \beta^j, \gamma^j_T, \xi\}$ *following the approach of Allen, Arkolakis and Li (2020), i.e, the spectral radius of the coefficient matrix is less or equal than 1.*

Online Appendix(1.C.3) presents details of my augments and a set of conditions for the steady state equilibrium.

Discussions of the assumptions. Several assumptions in the model should be emphasized. First, I assume that the worker choose location first and then the sector. Alternative ways are to model the location and sector decision simultaneously (Zárate, 2022) with a nested Gumbel distribution, or assume the worker chooses sector first and then location(Takeda, 2022). The first way will not lead to much difference to the final result, and the second generate different migration matrix for different sectors, amplifying the role of structural transformation. Second, since there are no land developers or housing market in this model, I assume the land is owned by local workers and the prices for consumption and production are the same, and the fixed land supply is equal to the demand from final consumers and producers. Including the housing production or land developer is a future plan.

1.3.5 The impacts of Migration Cost: A Two-location Example

Before proceeding to the calibration, I present some economic intuitions regarding the impacts of migration cost reduction using a simplified model that includes only two areas: urban and rural. The economy is assumed to be frictionless,i.e, without costs of trade, sector switching or migration costs. Productivities are identical across sectors and areas, and amenities are also uniform. The sole difference is that education costs in the rural area are twice those in the urban area, implicitly suggesting a higher skill share in urban areas. This disparity in educational cost, or quality, incentivizes workers to migrate from rural to urban areas. Additionally, it is assumed that migrants face an extra education cost equivalent to that in urban areas. For this section, I set the parameters of the PIGL utility to align with those estimated by Song et al. (2020).[16] Skill intensity is highest in the service sector, followed by the industrial and agricultural sectors. In the baseline scenario, everyone possesses urban hukou, so additional educational costs do not take effect, and there are no costs related to child-placement.[17]

[16]The parameters are set as follows: $\epsilon = 0.4$ and $\gamma_{ag} = 0.48, \gamma_G = 0.52, \gamma_S = -1$, which are similar to the parameters used for calibration.

[17]It is important to note that only skilled workers incur educational costs, resulting in their initial steady-state values being higher than those of unskilled workers.

Increasing the Rural-Urban Migration Costs

Proposition.4.1 Increasing rural-urban migration costs (a) disproportionately diminishes individual welfare in rural areas, as evidenced by $\frac{\partial V(r,g)}{\partial C_{ru}} < 0$*, widening the welfare gap between skilled and unskilled individuals; (b) hampers the educational mobility of local urban residents while raising that of urban migrants, consequently diminishing overall educational mobility at the national level; (c) prevents structural transformation and urbanization.*

Proposition.4.2 Introducing migrant children cost (a) decreases the individual welfare levels and enlarges the welfare gap between skill groups, (b) reduces the educational mobility of all groups, especially that of urban migrants.

Panel(a)-(f) in Figure 1.6 show the impacts of increasing rural-urban migration costs on welfare, educational mobility change and structural transformation. rural workers who would have otherwise migrated to urban areas for utility maximization opt to stay in rural regions, resulting in decreased welfare levels. Nationally, the decline in the welfare of rural workers, coupled with their reduced likelihood of becoming skilled workers, accelerates the overall weighted average decline in unskilled workers' welfare compared to that of skilled workers. This dynamic amplifies the welfare gap.

This increasing welfare gap in the rural also encourages people to become skilled workers, as the orange dot line in Panel(c) shows, though to a moderate degree. Conversely, there is a significant discrepancy in educational mobility between local residents and migrants in urban areas, even though the welfare gap remains relatively constant as migration costs rise. Higher migration barriers filter out less productive workers, resulting in an average higher productivity of those who still migrate to urban areas compared to a frictionless environment. This heightened productivity translates to increased income, fostering greater educational investment in children and subsequently enhancing educational mobility. While the educational investment of urban locals decreases slightly due to labor market adjustments, resulting in a smaller educational gap between urban migrants and locals, national-level educational mobility experiences a substantial decline. This is attributed to more workers choosing to remain in rural areas, where they face higher education costs, negatively impacting overall national educational mobility. The increasing migration costs also decreases the non-agricultural employment share and urbanization, as Panel(e) and Panel(f) show.

Panel (a)-(d) in Figure 1.7 present the effects of increasing rural-urban migration costs when migrant costs are also considered. These additional costs result in a universal decline in individual welfare, with rural areas experiencing more significant losses than urban areas. Educational mobility diminishes across all groups, with urban migrants facing the most substantial negative impact, leading to a widened educational gap between migrants and locals in urban areas.

Rising the Probability of obtaining Hukou

Proposition.4.3. Rising the probability of obtaining local hukou (a). increases the welfare of both groups, with a particularly pronounced improvement for unskilled workers; and (b) boosts educational mobility for both groups, especially among migrants. However, (c) the introduction of an additional cost for migrant children slightly diminishes these positive impacts.

Panel (a)-(f) in Figure 1.8 display the impacts of rising hukou obtaining probability from 0 to 1.In Panel(b), where an additional cost for migrant children is considered, the enhancement in the welfare of unskilled workers diminishes, consequently widening the welfare gap. The smaller welfare enhancement of unskilled workers is primarily driven by the misallocation of unskilled labor, as individual welfare does not change much. The introduced cost also reduces the initial level of educational mobility for both groups, particularly affecting migrant children. Individual educational mobility experiences minimal change with the increasing probability, therefore rising in educational mobility of locals at the national level is attributed to the growing number of urban workers, who exhibit the highest educational mobility. The shift in sector composition is moderate, intensifying to some extent with the introduction of an additional cost for migrant children.

These insights illustrate how net migration costs and the hukou threshold affect critical outcomes at both the individual and aggregate levels, and how these impacts vary with migrant children's costs. In practice, the asymmetry in cost changes across different groups leads to a shifting welfare gap, which adds another dimension to changes in educational mobility. Additionally, the distribution of educational resources between rural and urban areas significantly influences these effects. The toy model also highlights that the benefits of reducing any cost diminish when education costs are equalized between the two areas, as detailed in Appendix (1.A).

1.4 Taking the Model to Data

This section discusses the procedure for calibrating the structural parameters and associated costs based on the 2005 mini-census, the 2010 census, and Chinese Statistical Yearbooks for 59 provincial area cells.[18] The Chinese census, conducted by the National Bureau of Statistics of China (NBS) every ten years, is a comprehensive demographic survey. In addition to these decadal censuses, the NBS conducts sample surveys, such as the 2005 and 2015 1% mini-censuses, to collect detailed demographic and socioeconomic data from a representative sample of the population. Importantly, the census covers the entire population at their current place of residence, irrespective of their household registration (hukou) status, including migrants.

The census data encompasses a wide range of information, including occupation, industry, income, ethnicity, education level, and housing characteristics. However, it is worth noting that only the 2005 mini-census includes data on income and housing value. The census also provides valuable insights into migration history, including the county of registration, the province of residence five years prior, and the type of registration (agricultural hukou or not). While the 2000 census offers information on the county of origin, it lacks detailed hukou data. Only the 2000 and 2010 censuses contain information on the province of birth.

[18] Data for Tibet (Xizang) Province is missing and therefore excluded from the analysis.

Three key parameters govern the migration barriers: the probability of obtaining local hukou, θ_d^g; inferred net migration costs, C_{od}^g; and child-placement costs, $\{t^g(o|LB), t^g(d|MG)\}$. The migrants-local gaps related to education costs, λ_e, and amenities, $\chi(g)$, are absorbed in the probability of obtaining local hukou.

The calibration proceeds in two parts. First, I calibrate some elasticities, including the sector labor supply elasticity, η; migration elasticity, σ_z^g; and education elasticity, σ_g. I also recover trade costs and productivities following Tombe and Zhu (2019)'s strategy independently at this step. Then, I infer the net migration costs, amenities, child-placement costs, and high school education gap using the observed wage and labor allocations, as well as the parameters calibrated in the first step. Following Eckert and Kleineberg (2021), I assume that parents are naive and expect local values to remain the same in the next generation, such that $V_{t+1}(o,g) = V_t(o,g)$. This allows me to exploit the fixed point property of the value function and use an inner-loop algorithm.[19] Because wage information is missing in the 2010 data, I first impute the wage using City Statistical Yearbooks and then conduct a similar analysis (see Appendix 1.B). The calibrated parameters are displayed in Table 1.4.

1.4.1 Calibration of Parameters

Demand, Production and Hukou Probability. The PIGL preference is characterized by the following parameters: $\{\omega^F, \omega^G, \omega^S, \gamma_F, \gamma_G, \gamma_S, \epsilon, \alpha\}$. All parameters except α are borrowed from Chen et al. (2022)[20], while α is calibrated to match the expenditure share on non-housing goods from the Statistical Yearbook. Production function parameters $\{\beta_l, \beta_k\}$ for different sectors are also taken from Chen et al. (2022), who estimate these parameters using NBS data based on a growth accounting framework. The elasticity of substitution between high and low-skilled workers, ρ, is assigned a value of 1.4, following Katz and Murphy (1992), which has been widely used in previous literature. The agglomeration effects,

[19]The calibration does not require the economy to be in a steady state, and I interpret the data to reflect a transitional period in our model.

[20]They calibrate all the related parameters using the CHIP dataset.

captured by γ_T^j, are borrowed from Takeda (2022), who estimated different productivity elasticities with respect to local employment density for different sectors. On average, I use values of 0 for the agricultural sector, 0.075 for the industrial sector, and 0.16 for the service sector. I calculate the hukou obtaining probability θ_d^g as the ratio of migrants (defined according to their birthplaces) who obtain local hukou at the time of survey, using data from the 2000 and 2010 censuses.

Trade Cost and Local Productivity. I begin by setting the trade elasticity to 4, consistent with Tombe and Zhu (2019). I then calibrate the parameters related to trade costs for tradable industries $\{\tau_{od}^j\}$ where $j \in \{G, F\}$, and local productivities $\{A_d^j\}$ for $j \in \{G, F, S\}$ at the province level. The trade cost can be decomposed into two parts: a symmetric part and a location-specific exporting cost. Specifically:

$$\tau_{od}^j = t_{od}^j t_o^j = \bar{\tau}_{od}^j \sqrt{\frac{t_o^j}{t_d^j}}$$

where $\bar{\tau}_{od}^j = \sqrt{\tau_{od}^j \tau_{do}^j} = (\frac{\pi_{oo}^j \pi_{dd}^j}{\pi_{od}^j \pi_{do}^j})^{\frac{1}{2\theta}}$ is the symmetric trade cost between o and d for sector j, which can be estimated from observed trade shares. I then simultaneously calibrate the local productivity A_d^j and location-specific export cost. This is done by choosing the vector of $\{A_d^j, t_d^j\}$, calculating the corresponding trade share, and minimizing the distance between the data and calibrated trade share for $j \in \{G, F\}$. For the tertiary sector, as the data on total output, labor, and land can be observed from the Statistical Yearbook, the productivity can be directly calculated as:

$$\ln A_d^S = \ln Y_d^S - \beta_l \ln E_{dS} - \beta_h \ln H_{dS} - \rho \ln L_d$$

With these calculations, I can obtain the price index. Combined with the PIGL specification and observed wage data, the utility u_{dj}^s can be calculated up to a scale.

Sector Supply elasticity and Sector-Switching Costs. I estimate the sector supply elasticity η using pooled data from the 2002, 2013, and 2018 CHIP surveys, which are repeated cross-sectional surveys closely related to the household surveys conducted by the NBS. Using the following estimable regression model, the elasticities can be derived from equation (1.15):

$$k^s_{dq,t}(j) = \exp(\beta \tilde{c}_{dq,t}(j) + \gamma_{djs} + \gamma_{dqst}) + \epsilon_{dqtj} \tag{1.20}$$

where $k^s_{dq,t}(j)$ is the sector employment share at location-migration status and skill level, $\tilde{c}_{dq,t}(j)$ is the deflated weighted average of local consumption raised to power ϵ according to the PIGL utility function, γ_{djs} and γ_{dqst} are the location-sector-skill fixed effects and location-migration-skill-time fixed effects, respectively. The parameter of interest is $\eta = \frac{1}{\beta}$. I cluster the standard errors at the location level. Results are shown in Table 1.5. My estimate using PPML is $\eta = 1.43$, somewhat close to Galle, Rodríguez-Clare and Yi (2023)'s estimate of 2.

After calibrating the supply elasticity, I recover the switching costs for workers of skill g to manufacture and service sectors, $\{m^g_d(MAN), m^g_d(SER)\}$, normalizing the agriculture sector cost to 0. I take a guess of the cost vector, calculate the sector employment share from equation (1.15), and then calibrate the corresponding cost by minimizing the distance between data and calibrated share. Note that while the switching costs only differ by skill, the equation calculates the skill-migration status value, so I match the moments of aggregated sector share of skill g in d. Normalizing the costs of choosing the agricultural sector to 0 in all places, the costs of switching to non-agricultural sectors mostly fall in negative intervals in urban areas, implying a net gain from switching sectors in urban areas. This corresponds to the reality that over 60% of workers in rural areas work in the agricultural sector. The first two rows in Table 1.10 show great distinctions between different skill groups, sectors, and areas.[21] On average, switching to the service sector benefits all workers in urban areas, with skilled labor benefiting the most. In rural areas, however, the costs are positive and higher for unskilled workers. Switching to the industrial sector presents a similar pattern,

[21] I only show kernel density plots and summary table of means in this section; other detailed results are in the appendix.

despite benefiting less than switching to the service sector. In 2010, the distribution of all switching costs shifts to the left, reflecting decreasing switching costs from agriculture to other sectors over time.

Migration Elasticity. With the calibrated sector-switching cost, price, and utility, $\bar{U}_d^s(q)$ can be calculated using equation (1.16). Noting that parents consider their children's expected utility, I restrict the sample to those without children. Consequently, the migration costs calibrated here don't fully match the observed patterns. From the migration gravity equation (1.17), I recover the preference dispersion parameter σ_z^g by running the following regression separately for skilled and unskilled workers:

$$\frac{m_{od}^g}{m_{oo}^g} = \exp(\beta \bar{U}_d^q(g) + \Gamma X_d + \ln Dist_{pp'} X D_{sw} + \gamma_{pp'} + D_{sw} + \gamma_o) + \epsilon_{od}(q) \tag{1.21}$$

Following Tombe and Zhu (2019), I make some assumptions about migration costs for identification: 1. $\mathcal{C}_{od}$ can be absorbed by controlling for origin-destination province fixed effects $\gamma_{pp'}$, origin province-area fixed effects γ_o, and whether agricultural workers switch sectors D_{sw}; 2. The destination-area amenities $\ln B_{dj}$ can be absorbed by controlling for a series of local features X_d, and $E(\epsilon_{od}|Y_{od}) = 0$.

Table 1.6 shows the results. The dispersion parameter σ_s is obtained by taking the inverse of the coefficient β. To address potential endogeneity of utility (e.g., labor market structure and amenities at destinations), I use exogenous reduction in US-China tariffs, following Khanna et al. (2021)'s strategy as the instrumental variable, and for skilled workers it is the import tariff reduction during 2000-2006.

First-stage regressions show that both IVs are valid. The magnitude of these coefficients is larger compared to columns (1)-(4), possibly due to omitted variables at the destination. In addition to city-level initial conditions in 2000, I control for the standardized Reform Index during 2000-2005. I find a robust positive relationship between the reform degree and migration flow for skilled workers, whereas for unskilled workers, both the magnitude and significance are small.

Consistent with Fan (2019), who estimates a larger dispersion parameter for skilled workers, I use the IV results from columns (5) and (6) to pin down the parameters: $\sigma_z^h = 1/1.624 = 0.62, \sigma_z^l = 1/1.352 = 0.74$.[22] I also assume that locals enjoy a premium of local amenities, i.e., migrants receive only a proportion λ^s (not larger than 1) of local amenities, while locals can enjoy them fully.

Education elasticity. In this part, I specify the total education cost and estimate the education elasticity σ_g using CEPS data. Considering the different probabilities of obtaining local hukou $\theta_d(g)$, the total education cost for migrants in d is an expected value of natives and migrants: $\tilde{Z}_d^g(\text{Migrant}) = \theta_d(g) Z_o^g(\text{Loc}) + (1 - \theta_d(g)) Z_o^g(\text{NonLoc})$ The total education cost for people in location d, with skill g and migration status $q \in \{M, C\}$, increases with additional education costs λ_e paid by migrants and location-group specific costs $\bar{z}_d^g$, and decreases with human capital accumulation $k(d, g, n)$. Formally:

$$Z_d^g(n) = \bar{z}_d^g + \mathbb{I}(n = \text{NonLoc})\lambda_e(q) - k(d, g, n)$$

In the previous section, I estimated the group-specific human capital production function (1.1) that depends on children's hukou status, parental investment, school expenditure, and size. Using the education choice probability (1.11), I regress the expected high school attainment on standardized test scores, controlling for a set of individual variables:

$$\text{Pr}_i(\text{Expected\_HS} = 1) = \alpha \text{score}_i + X_i + \epsilon(i) \tag{1.22}$$

where α suggests the effect of standardized score on high school probability, and X_i includes student age, hukou property, gender, whether they are an only child, dialect proficiency, and parents' marital status. To address potential endogeneity, I also use the leave-one-out

[22] Note that my estimates differ from Tombe and Zhu (2019) and Fan (2019)'s as I use the expected utility calculated from previous steps, so the distribution varies largely from those using real income in regression.

measure of classmates' average test score as an instrument and run a Logit regression at the second step. The results in Table 1.7 show that the education elasticity is similar using both methods, and the coefficients do not significantly differ by skill group.[23] I use the IV result and calculate the elasticity as $\sigma_s = 1/1.236 = 0.81$.

1.4.2 Inferring Costs

In this section, I infer the critical components of the total migration barrier. The process consists of three main steps. First, I estimate the net migration cost by specifying a function that minimizes the distance between observed data and calibrated migration flows. Second, using the estimated parameters from the first step, I calibrate the migration costs and subsequently back out the amenities. Finally, I employ an inner loop algorithm to invert the model and infer the migrant children and education gap. This approach allows for a comprehensive analysis of the migration barriers, progressing from basic cost estimation to more complex inferences about migrant children and education disparities.

Net Migration Costs. Net migration costs are composed of three main components: unchangeable costs such as geographic and cultural distance between origin and destination, time-varying costs encompassing various origin-destination characteristics that may change over time, and sector-switching costs incurred when migrants move between different economic sectors. To estimate the coefficients of the specified migration cost equation, I employ a nested nonlinear least squares procedure, following a method similar to Fan (2019).

This approach involves two nested loops. In the outer loop, I select the parameters $\{\beta_i, \alpha_i\}$, which are the coefficients of the migration cost specification, and γ^s, which governs the local premium for accessing amenities. The amenity function for migrants is defined as $B_d^g(M) = \theta_d^g \bar{B}_d^g + (1 - \theta_d^g)\chi(g)\bar{B}_d^g$, where $\chi(g)$ represents the premium for locals and is constrained to be no less than 1 in urban areas. Within the inner loop, I determine the local amenities $\bar{B}_d^g$. The goal is to ensure that the total in-migration stock in each cell precisely

[23] To meet the condition of unique equilibrium that the elasticity should be less than 1, I multiply the score by 0.6.

matches the observed data, given the estimated migration costs and the guessed premium parameter for year t. This is achieved by selecting $\bar{B}_d^g$ to satisfy

$$||log(\sum_{o \in N} \hat{L}^g_{od,t}) - log(\sum_{o \in N} L^g_{od,t})|| = 0$$

where $\hat{L}^g_{od,t}$ represents the estimated migration flow and $L^g_{od,t}$ is the observed data. This method of estimation, as opposed to direct recovery from model inversion, offers the key advantage of distinguishing between unchangeable and changeable components of migration costs, which is particularly valuable when conducting counterfactual analyses. The number of moments in this equation exactly equals the number of unknowns, allowing for a unique determination of the amenities and providing a robust foundation for further analysis of migration patterns and policy impacts.

Child-Placement Costs. I categorize child-placement costs into two types: (1) left-behind children costs and (2) migrant children costs, matching them to two sets of moments in the data. Table 1.10 displays the distribution of left-behind and migrant children costs for different groups in 2005 and 2010, while Figure (1.A.5) illustrates their distribution for each year. First, Skilled workers have lower costs for taking children with them, whereas unskilled workers have lower costs for leaving children behind. Second, Costs in rural areas are significantly lower than in urban areas. Third. In 2010, both types of costs decrease modestly compared to 2005, especially for skilled workers. The spatial distribution in Figure (1.A.5) reveals that coastal areas, Beijing, and Shanghai have particularly high costs across all categories. These patterns correspond to the fact that skilled migrant workers in urban areas are more likely to bring children with them, and mega-cities have high child-placement costs overall.

Education Costs. Figure 1.A.4 shows the kernel distribution of education costs for 2005 and 2010. We find that, on average, unskilled families face higher education costs than skilled families, and costs in rural areas exceed those in urban areas. Comparing the two panels reveals that the overall distribution of costs shifts leftward in 2010, suggesting an increase in education levels among younger cohorts over this period. This observation is supported by the average values presented in Table 1.10. Figure 1.A.6 illustrates the spatial distribution of rural and urban education costs for unskilled and skilled families. For both groups, exogenous education costs are higher in inland areas, particularly in western and northeastern regions. Within-area costs are similar for skilled and unskilled families, but between-area costs display some distinctions. For example, exogenous education costs are especially high in rural areas of Qinghai, while Sichuan has, on average, higher costs in urban areas.

Amenities and Productivities. The last two rows in Table 1.10 indicate that amenities are increasing over time, with the gap between rural and urban areas widening. The upper half of Figure 1.A.7 shows the spatial distribution of amenities aggregated at the provincial level, using urban population share as a weight for different years. The lower half displays the distribution for 2005 and 2010.

For both years, amenities are higher in coastal provinces. However, in 2010, amenities appear to be higher in developing regions such as Xinjiang and Inner Mongolia compared to 2005. Panels (c) and (d) show that amenities for unskilled workers are, on average, lower than those for skilled workers, with rural amenities falling mostly in negative ranges. The gap between different skill groups within the same area decreases from 2005 to 2010, whereas the gap between different areas remains significant.

Table 1.A.4 presents the relationship between model-derived amenities and local characteristics in 2005. The first column includes only urban areas, while the second column shows weighted average amenities using the corresponding skill share and urban share. OLS results indicate that the log of total road area, number of healthcare workers, house area per capita, and public expenditure per capita are significantly positively related to both amenity measures. Pollution is negatively related to amenities, though the relationship is not statistically significant. For urban amenities, the coefficient and significance of log total

water use are larger than those of aggregated provincial amenities.

Figure 1.A.8 illustrates the distribution of productivities across regions for different sectors, with international productivities normalized to 1 for each sector. We observe that agricultural productivities are higher in southwestern and inland provinces, industrial productivities are higher in northern and southern China, and service productivities are higher in coastal areas. Figure 1.A.9 confirms the positive relationship between local GDP and productivities for both years and sectors.

1.4.3 Validation

We validate our model using two approaches. First, we compare model-predicted transition paths of aggregate statistics over a 20-year period with national-level time-series data. Second, we examine the cross-regional distribution of key moments in 2005 and 2010, comparing model predictions with empirical data. To conduct these tests, we compute the transition path to steady state, using the 2000 economy as the initial state and incorporating calibrated fundamentals from 2005 and 2010 data.[24]

Figure 1.16 compares model-predicted transition paths of sector and urban employment shares with empirical data from 2000 to 2020. The model closely tracks observed trends. Empirically, the agriculture share falls to 24.85% and the service sector share rises to 45%; our model predicts 26.5% and 45%, respectively. The urban population share increases from 36% to 61.4% in the data, while our model predicts 65% by 2020, suggesting actual urbanization slightly lags the model's predictions.

We next examine cross-regional distributions of key moments in 2005 and 2010. Figure 1.17 shows a strong positive relationship between observed and predicted distributions of sector employment shares, and Table 1.11 confirms similar mean values for sector shares in both years.

Figure 1.18 presents the relationship between data and model predictions for skilled labor

[24]The steady state is calculated using 2005 calibrated fundamentals. For the transition path, we update to 2010 fundamentals in the latter period.

distribution. Panel (a) depicts the distribution of each region's share in national skilled labor, while panel (b) shows the skilled labor share in local labor markets. Both panels exhibit strong positive correlations (> 0.9) between data and model predictions, with similar mean, median, and maximum values.

Figure 1.19 illustrates the distribution of high school attainment probabilities for young cohorts from different family backgrounds. All panels demonstrate strong positive relationships between data and model predictions. Table 1.12 reports mean probabilities of high school attainment by family background and year. Odd-numbered columns represent probabilities for individuals from unskilled families, while even-numbered columns for those from skilled families. Both data and model show increasing trends in high school attainment over time, though observed magnitudes are generally smaller than model predictions.

This validation exercise suggests that our model captures key features of China's economic transition, both in terms of aggregate trends and cross-regional distributions. The model's predictions align closely with observed data, providing a solid foundation for subsequent counterfactual analyses.

1.5 Counterfactual Analysis

This section presents counterfactual experiments to quantify the impact of migration-related policies on structural transformation, educational mobility, welfare, and inequality. Our analysis focuses on steady-state outcomes and transition paths, measuring welfare and educational mobility at the national level.[25] We consider three main scenarios: (1) removal of all hukou thresholds, (2) elimination of migrant children costs, and (3) a 30% reduction in variable migration costs.[26] We also examine how these effects interact with equal allocation

[25]We measure national-level aggregate welfare and educational mobility using: $W_j = \frac{\sum_{i \in J} L_i(j) V_j(i)}{\sum_{i \in J} L_j(i)}$, where 'i' denotes the unit in subgroup 'j.' The log change in W_j can be decomposed into intensive changes in $V_j(i)$ and extensive changes in total L_j: $d \ln W_j = \sum_{i \in J}^{N} s_j(i) d \ln V_j(i) + (\sum_{i}^{N} s_j(i) d \ln L_j(i) - d \ln L_j^{total})$. This formulation captures both individual-level changes and compositional effects.

[26]We retain costs associated with geographic and cultural distance while reducing other costs.

of educational resources between rural and urban areas.

Our key findings reveal that any reduction in migration costs prompts structural transformation and enhances educational mobility. The aggregate welfare of unskilled workers improves at the national level under all scenarios of reduced migration costs. Skilled workers, however, experience larger locational welfare gains compared to unskilled workers. Educational mobility effects vary substantially across regions, with northeastern areas generally benefiting the most. We observe that inter-group inequality decreases between skill groups, but intra-group spatial inequality increases.

When allocating educational resources equally across rural and urban areas, we find that the relative welfare improvement for unskilled workers becomes smaller, and educational mobility is enhanced less compared to the unequal allocation scenario. This provides valuable insights into the interplay between educational resource allocation and the consequences of migration.

These results highlight the complex relationship between migration policies, educational resource allocation, and economic outcomes. They suggest that while reducing migration barriers generally promotes economic development and mobility, the distributional consequences are nuanced and vary across skill groups and regions.

Tables 1.14 and 1.15 summarize results for all counterfactual experiments, while Figure 1.20 illustrates transition paths under the unequal allocation scenario. The following subsections provide detailed analysis of each counterfactual scenario, examining the mechanisms driving these results and their implications for policy.

1.5.1 Quantifying the Child-Placement Mechanism

We first consider a frictionless scenario where all migrants bring their children to their destinations, holding other conditions constant. As shown in Column (1) of Table 1.13, this scenario leads to a 5.7% increase in national average welfare and a 31.6% increase for unskilled workers. Structural transformation and urbanization rates both grow by approximately 8%, while educational mobility for urban migrants nearly doubles. To isolate the role of educational mobility, we shut down this channel while maintaining family migration (Column 2). This leads to substantial decreases in average welfare, service employment share (32.6% decline), urbanization rate (23.5% decline), and skilled labor share (42% decline) compared to the baseline. These results suggest that the positive impacts of family migration on welfare and structural transformation primarily operate through enhanced intergenerational educational mobility. Column (3) shows that removing hukou thresholds further improves welfare and structural transformation, with educational mobility for urban migrants quadrupling. This highlights how hukou-related costs impede educational mobility and slow potential structural transformation.

1.5.2 Impacts of Migration Cost Reduction

Removing Hukou Threshold. We examine the counterfactual scenario of removing all restrictions on obtaining local hukou. Results are presented in Column (1) of Table 1.14 and Columns (1)-(4) in Panel (A) of Table 1.15. At the national level, we observe moderate welfare increases, with unskilled workers experiencing a 15% rise. Locational welfare improvements are slightly higher, favoring skilled workers over unskilled workers. This suggests that most of the welfare enhancement comes from the extensive margin, i.e., a decrease in unskilled workers. Non-agricultural employment share increases by 4.6%, primarily driven by service sector growth, with structural transformation more pronounced in western and northeastern regions. Educational mobility more than doubles for urban migrants nationally, with a 24.7% increase in eastern regions and a 27.5% increase in northeastern regions. The substantial growth in eastern areas suggests that high hukou barriers in these provinces have significantly hindered educational mobility. Inequality, as measured by the Theil index, increases by 30% nationally, with eastern areas experiencing the largest increase (23.2%), followed by western regions (21.7%). These results underscore the complex effects of hukou reform on welfare, structural transformation, and inequality, highlighting that while removing hukou thresholds generally improves welfare and educational mobility, it also exacerbates spatial inequality, particularly in more developed regions.

Eliminating All Migrant Children Cost. We examine the effects of eliminating all migrant children costs while keeping left-behind costs constant. Column(3) of Table 1.14 and Column(5)-(8) of Table 1.15 present the results at the weighted-aggregate national level and average locational level, respectively. National welfare decreases by 6.5%, with unskilled workers' welfare rising by 23.6% and skilled workers' falling by 10%. Locational average changes are more positive for skilled workers but negative for unskilled workers in western and north-eastern areas. This reduction prompts structural transformation by 6.3% nationally, with the largest increase in north-eastern areas. Educational mobility enhances by 12.5% for urban migrant children and up to 15% for rural left-behind children, with the most significant increase (19.4%) in north-eastern areas. Rural natives also experience growing educational mobility due to increased welfare for skilled labor in rural areas in the steady state. Inequality rises by 20% nationally, with western areas increasing the most.

Lowering Net Migration Cost. We reduce origin-destination pairwise migration costs by 30%, excluding geographic distance costs. Results are shown in Column(5) of Table 1.14 and Column(9)-(12) in Table 1.15. National average welfare decreases by 7.2%, with a 27.1% increase for unskilled workers and an 11% decrease for skilled workers. Across the country, unskilled workers' average welfare declines dramatically, while skilled workers experience moderate growth. The share of skilled workers, non-agricultural employment, and urban population increase substantially at the locational level. Inequality rises fivefold nationally and over quadruples in eastern and western areas. Educational mobility for urban migrants doubles at the national level and increases significantly for rural left-behind and rural natives, with mobility in north-eastern regions doubling for all rural residents. This new equilibrium with low migration frictions sees increased welfare for skilled labor in rural areas as skilled workers migrate to urban areas, driving structural transformation, urbanization, and educational mobility.

Dynamic Paths. To examine the role of labor dynamics in shaping the persistent and heterogeneous impact of migration cost reduction, we analyze the impulse responses of various outcomes, assuming the final period reaches a new steady state. Figure 1.20, panels (a)-(g), illustrates the dynamics of changes in average welfare, sector composition, educational mobility for different family types, and the overall Theil Index across periods, compared to the baseline path. Most outcomes, except upward mobility for migrant families, show the most significant impacts in the initial periods, with effects diminishing over time. This pattern is more pronounced when combining all cost reductions. Consistent with steady-state comparisons, the service share increase surpasses the industrial share change in later periods, despite a more dramatic initial drop. Over time, the average welfare of unskilled workers increases more than that of skilled workers, while the change in educational upward mobility for migrant families continues to grow and remains higher than for local families. The Theil Index initially drops and then increases when reducing net migration costs, moderately decreases when eliminating migrant-children costs, and remains steady when raising Hukou probability. Combining all reductions amplifies these effects by nearly threefold, with trends becoming more pronounced in later periods. These dynamic paths highlight the complex and evolving nature of the impacts of migration cost reductions on various economic and social outcomes.

1.5.3 Impacts under Equal Educational Resource Allocation

The unequal allocation of educational resources between rural and urban areas significantly influences migration patterns. Thus, it is essential to understand how the impact of reducing migration costs would change in a scenario where the initial allocation of educational resources between rural and urban areas is equal. I conduct the same set of counterfactual experiments as in the previous section. The results are presented in Table 1.14 and Panel B of Table 1.15.

Before proceeding to the analysis, it is important to highlight the differences between the two baselines, as shown in the last column of Table 1.14. Notable outcomes arise in a scenario where educational resources are uniformly distributed across rural and urban areas within a province. First, average welfare declines by 18% compared to the actual case, while the welfare of unskilled workers increases by 10.7%, in contrast to a 20% decrease in the welfare of skilled workers. Overall inequality decreases by 40%, indicating a reduced gap between various groups, with inequality within the skilled group also falling by 40%. Additionally, the service share and urban share decrease by 5.6% and 1.3%, respectively. These results suggest a more equal welfare distribution across regions and groups, accompanied by elevated education levels in rural areas at the cost of slower structural transformation and urbanization.

When removing the hukou thresholds in all regions, Column (2) in Table 1.14 shows that weighted-average welfare increases significantly by 21.25%, primarily due to substantial improvements in the welfare of skilled workers (26%), resulting in a larger welfare gap between skilled and unskilled workers at the national level. However, Panel B in Table 1.15 indicates that locational welfare changes are similar to the previous case. One reason for these distinct results is the substantial change in urbanization, with an initially higher rate of skilled workers in rural areas. [27] Compared to the unequal situation, the growth in the service employment share doubles at the national level due to labor reallocation across regions. Regarding educational mobility, the national-level enhancement for urban migrants is only half of that in the unequal case, while the locational changes are similar. Although national-level inequality still increases substantially, the inequality within each area drops by half.

Column (4) in Table 1.14 shows that the welfare change and structural transformation follow a similar pattern when eliminating all migrant children costs, with national-level welfare increasing by 13.6% and the non-agriculture share growing by over 13%. Urbanization increases substantially by 20.4%. However, national-level educational mobility for urban

[27] According to footnote 37, the national-level increase comes from the second term.

migrants increases by 14.3%, while it decreases slightly for rural left-behind children, and locational outcome changes are similar to the equal case. National overall inequality increases by 64%, more than three times that in the first case (19%). The eastern regions experience a similar magnitude increase in inequality, in contrast to a rather moderate increase in the northeastern regions. These results suggest that the different patterns at the national level primarily stem from the reallocation of skilled workers from rural to urban areas.

Lastly, when lowering time-variant net migration costs by 30%, Column (6) in Table 1.14 shows that national-level welfare increases by 10.3%, with a 6.4% increase in skilled workers and a 26.1% increase in unskilled workers. The non-agricultural employment share increases by 14%, with the share of the service sector growing by 11.4%, and urbanization increases similarly to the elimination of migrant children costs. Compared to the case with unequal education costs, the improvement in educational mobility decreases for all children, showing diminishing marginal returns to migration cost reduction. However, Panel B of Table 1.15 suggests that the enhancement in average educational mobility of rural children varies across regions, with western regions experiencing a relative increase and other regions experiencing a decrease, especially the northeastern regions, compared to the case of equal education costs. This variation arises from the increasing welfare of skilled workers in rural areas with different shares across regions.

In summary, an equal distribution of educational resources across rural and urban areas within a province mediates the impacts of reducing migration costs at the national level, primarily through the reallocation of skilled workers from rural to urban areas. This mediating effect leads to less welfare improvement for unskilled workers relative to skilled workers, more spatial inequality, and smaller enhancements in educational mobility compared to the effects under the condition of unequal education costs. These results suggest that the allocation of educational resources and the reduction of migration costs are substitutes to some degree, and the effects of removing migration barriers are more significant where educational resources are allocated unequally. [28]

1.6 Conclusion

In this research, I examine the impact of internal migration on educational transmission, structural transformation, and the welfare effects of removing migration barriers in China. Utilizing census population data, the empirical findings indicate that being left-behind or lacking local hukou is associated with worse education performance of the youth. To evaluate the impacts of reform policies and to decompose the contributions of various mechanisms, I develop a tractable quantitative spatial equilibrium model with overlapping generations (OLG). This model incorporates the frictional movement of workers across regions and sectors, non-homothetic preferences, productivity spillovers, and congestion effects.

The fundamental mechanism of the model is rooted in parental decision-making: parents must not only choose their location and sector but also decide whether to relocate with their children. Migrant children typically receive a lower quality of education compared to their local counterparts, while left-behind children experience the adverse effects of parental separation. Factors such as migration costs, location-specific child-placement costs, and educational opportunity costs significantly influence the transmission of human capital, which is integrated into the forward-looking objective function of the older generation. Consequently, the OLG structure of the model facilitates an analysis of the dynamics of structural transformation, spatial allocation, and the educational attainment of workers over an extended period.

To calibrate the model, I synthesize multiple sources of micro survey data and utilize provincial-level data to derive fundamental parameters and various costs. I then conduct several counterfactual experiments regarding the reduction of migration costs. The results demonstrate that allowing all parents to move with their children is essential for promoting

[28] Equal distribution across provinces or skill groups also shows similar mediating effects; additional results are available upon request.

educational mobility, thereby accelerating structural transformation. Furthermore, any reduction in migration costs enhances welfare for unskilled labor at the national level, despite significant regional disparities. Such reductions also stimulate structural transformation, urbanization, and educational mobility, albeit at the cost of increasing spatial inequality. Notably, increasing the probability of obtaining local hukou substantially benefits urban migrants, with outcomes varying significantly across regions. Lastly, the advantages associated with migration cost reduction are attenuated when educational resources are more equitably allocated between rural and urban areas.

These findings underscore how migration barriers influence the long-term development trajectory of an economy and highlight the necessity of implementing comprehensive policies aimed at reducing inequality across regions and generations. The proposed model can be extended to quantify the effects of various shocks, including infrastructures and trade liberalization, on local economies and workers over the long term. Despite the presence of negative congestion spillovers within the model, a limitation is the absence of an explicit housing market and local government considerations, both of which play critical roles in influencing workers' migration choices (Garriga et al., 2023). Additionally, the model could be calibrated using finer geographic units, such as the prefecture level, contingent upon the availability of detailed data. This approach would yield more meaningful policy recommendations to equalize opportunities across locations within countries, which is vital for the sustainable long-term development of a nation.

Table 1.1: Summary Statistics

	Migrants		Left-behind		Native		T-test	
	Mean	Sd	Mean	Sd	Mean	Sd	Migrant	Left-behind
Expected High School	0.84	0.36	0.78	0.41	0.84	0.37	0.0186**	0.043***
Score	-0.057	0.8	-0.186	0.85	0.05	0.87	0.084**	0.19***
log(*education_invest*)	4.01	3.55	4.10	3.57	3.64	3.56	-0.14	-0.179
Gender (1=Boy)	0.45	0.50	0.44	0.50	0.49	0.50	0.0167	0.0477**
Age	13.69	0.93	13.73	1.11	13.57	0.92	-0.077***	0.000
Hukou Property	0.63	0.48	0.68	0.47	0.54	0.50	-0.131***	-0.123***
Dummy for the Only Child	0.33	0.47	0.26	0.44	0.47	0.50	0.141***	0.164***
Dummy for Parents' Marriage	0.93	0.25	1.00	0.00	0.89	0.32	-0.027***	-0.106***
Proficiency in Dialect (1 for totally unskilled)	3.42	1.49	4.26	1.10	4.21	1.14	0.833***	-0.145***
Dummy for Skilled Family	0.25	0.43	0.15	0.36	0.30	0.46	0.074***	0.110***
Migrant Peer(%)	0.46	0.40	0.12	0.18	0.15	0.19	-0.315***	0.115***
Left Behind Peer(%)	0.18	0.11	0.33	0.18	0.22	0.12	0.065***	-0.121***
log(*SchoolSize*)	6.82	0.69	6.73	0.87	6.88	0.75	0.203***	0.139***
log(*School_exp*)	6.21	1.82	6.26	1.26	6.32	1.24	0.262***	0.032
Observations	2096		1223		6592		9748	9748

Notes: This table presents the mean and standard deviation of a set of variables by three exclusive groups. *education_expenditure* is the education expenditure spent by the parents, including the fee paid to school and additional fee for extracurricular activities. Dummy for Skilled Family is set to one if at least one of the parents has equal or above high school degree.The proportion of migrant peers and left-behind peers are defined following Huang (2022). The last two columns show the t-test between migrant and non-migrant children, and left-behind and non-left-behind children.$* < 0.1, ** < 0.05, *** < 0.1$.

Table 1.2: Results on Education Outcomes

	Standardized Score				Pr(Expected High School =1)	
	(1) Skilled	(2) Unskilled	(3) Skilled	(4) Unskilled	(5) Skilled	(6) Unskilled
log($education\_invest$)	0.023***	0.022***	0.028***	0.026***	0.026	0.065***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.03)	(0.02)
Migrant	-0.188**	0.019	-0.150*	-0.030	0.18	0.15
	(0.06)	(0.06)	(0.07)	(0.05)	(0.08)	(0.03)
Left-behind	0.005	-0.080**	0.062	-0.087*	-0.58	-0.272**
	(0.08)	(0.03)	(0.09)	(0.04)	(0.09)	(0.04)
School Characteristics						
log($School\_EXP$)			0.175**	0.074**		
			(0.05)	(0.02)		
log($SchoolSize$)			0.415***	0.147		
			(0.13)	(0.12)		
FE	Class X Year	Class X Year	County X Year	County X Year	Class X Year	Class X Year
Individual Controls	Y	Y	Y	Y	Y	Y
Class Controls	N	N	Y	Y	N	N
School Controls	N	N	Y	Y	N	N
N	2591	5505	2571	4863	1842	4883
adj. R^2	0.3310	0.2806	0.2769	0.1989	0.1172	0.1094

Notes: This table reports the weighted estimates of the (1.1) with two outcomes, based on the most restrictive definition of random sample. The results using alternative random sample that only depend on teacher's answer is on appendix (**??**). The dependent variable for Column (1)-(4) regressions is the standardized test score using OLS, and for Column (5)(6) is the expected high school attainment using Logit regression. I pool the data from two years together and only use the randomly arranged sample. Individual controls include student age, Hukou property, gender, whether he or she is the only child, dialect proficiency, parents' marriage status. The set of class controls includes the education level, gender and education experience of head teacher, and the share of migration peers as well as left-behind peers. School controls include the share of native students, whether the migrant students receive subsidy, and school's rank in this district. Column (1)(3)(5) regress on the sample from skilled families while column (2)(4)(6) regress on those from unskilled families. Column (1)(2)(5)(6) control for the class and year FE, column (3)-(4) control for county and year FE, $* < 0.1, ** < 0.05, *** < 0.1$. Standard errors in parentheses, clustered at school level for column (1)-(2) and at county level for (3)-(6). I also use bootstrap for Column (5)(6), whose standard errors are shown on the appendix.

Table 1.3: Results of the Oster Test

Key Variables	Controls in the restricted set	Controls in the full set	δ
Skilled family: Migrant	Controls selected in baseline regression (-Left_behind)	All potential controls	3.8
Unskilled family: Left-behind	Controls selected in baseline regression(-Migrant)	All potential controls	1.3

Notes: Full controls include the controls in the baseline, plus the time since children come here, dummy indicator for whether parents often argue, and categorical variable for health condition. First row only uses the children from skilled families and the second row uses those from unskilled families. Each regression only contains one endogenous variable: migrant or left_behind, different from the baseline.

Table 1.4: Summary of Parameters

Parameters	Value	Source	Meaning	Method
σ_s	0.83	CEPS	taste shock for HS dispersion	RF
$\lambda_{rr,t}, \lambda_{ub,t}$	0.33,1.5;0.5,1.3	Census2005,2010	additional costs migrants pay for education	GMM
σ_d^h, σ_d^l	0.62,0.74	Census2005	preference draw dispersion	RF
η_j	3.52	CHIP 2003,2008,2013	sector productivity draw dispersion	RF
Θ	table(1.2)	CEPS	Human Capital Production Function Coefs	RF
λ_d	location-specific	Census 2005	factor shares in total wage bill	Direct Estimate
$\theta_{hk,d}^g$	mean$_{rr} = 0.7; mean_{ub} = 0.3$	Census 2000,2010	probability of obtaining local Hukou	Direct Estimate
$\alpha, \beta \in \Gamma$	table(1.A.3)	census 2005 and 2010	parameters of migration cost function	GMM
α	0.87	CSY	match data of housing expenditure	Direct Estimate
θ	4	Standard Literature	elas of trade	Borrowed
ρ	1.4	Katz and Murphy (1992)	Elas of subsitution of H-L labor	Borrowed
γ_T^j	AG:0;IND:0.075;SER:0.16	Takeda (2022)	spillover of productivity	Borrowed
ξ	-0.3	Li (2022)	congestion paramter	Borrowed
ϵ	0.375	Chen et al. (2022))	Engel elasticity	Borrowed
ω_j	0.01,0.37,0.62	Chen et al. (2022)	Preferencce Parameter	Borrowed
γ_j	0.48,0.52,-1	Chen et al. (2022))	Preferencce Parameter	Borrowed
β_l^j	0.5,0.59,0.75	Chen et al. (2022)	Share of labor used in sector	Borrowed
ν	0.3	Eckert and Kleineberg (2021)	altruistic parameter	Borrowed

Table 1.5: Regression Results for Labor supply elasticity

	(1) PPML	(2) OLS
$\tilde{c}$	0.696***	1.028***
	(0.18)	(0.26)
Loc-Sec-Skill-MIG FE	Y	Y
Loc-Time-Skill-MIG FE	Y	Y
Observations	962	962
Adjusted R^2		0.5879

Standard errors in parentheses and clustered at location level.
OLS results is regressed on the log of dependent variable.

Table 1.6: Migration Elasticity by Skill Group

	(1) PPML Skilled	(2) PPML Unskilled	(3) OLS Skilled	(4) OLS Unskilled	(5) IV Skilled	(6) IV Unskilled	(7)PPIV Skilled	(8)PPIV Unskilled
U	1.04***	1.068***	1.044***	0.924***	1.624***	1.352***	1.656***	0.98
	(0.08)	(0.2)	(0.16)	(0.44)	(0.4)	(0.44)	(0.2)	(0.64)
ReformIndex	0.166*	0.108	0.390***	0.122*	0.290*	0.098	0.088	0.124
	(0.09)	(0.07)	(0.11)	(0.07)	(0.16)	(0.08)	(0.08)	(0.11)
Switch X lndist	0.219***	0.178***	-0.090**	0.143***	-0.094**	0.140***	0.223***	0.181***
	(0.02)	(0.02)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)	(0.02)
X_d	Y	Y	Y	Y	Y	Y	Y	Y
OXD Prov FE	Y	Y	Y	Y	Y	Y	Y	Y
O X Switch	Y	Y	Y	Y	Y	Y	Y	Y
N	2300	2420	3600	3600	3600	3600	2300	2420
adj./Pseudo R^2	0.6476	0.6554	0.5732	0.5546	-0.0150	-0.2759	0.6456	0.6543
First-Stage Results: U								
Z					-8.9***	-22.13***		
					(2.16)	(6.25)		
K-P stats					21.66	12.6		

Standard errors in parentheses and clustered at destination level, Z are import tariff reduction and NTR gap, Reform Index are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, controls include log population, manufacture share in 2000 and illiteracy rate.

Table 1.7: Education Elasticity Estimation

	(1) Logit	(2) IV	(3) Logit
Score	1.134***	1.236***	1.212***
	(0.12)	(0.15)	(0.11)
Score X Skilled Family			-0.32
	(0.12)	(0.15)	(0.21)
First Stage			
IV		-44.459***	
		(1.89)	
First-Stage F		552	
Controls	Y	Y	Y
FE	Class X Year	Class X Year	Class X Year
Observations	7602	7602	7602
Adjusted/Pseudo R^2	0.154	0.95	0.1453

Notes: This table reports the estimation results for education taste dispersion parameter σ_g. IV uses the leave-one-out average standardized score of the student's classmates. Column (2) uses the predicted score for logit regression. Control sets are the same.$* < 0.1, ** < 0.05, *** < 0.1$. Standard errors in parentheses, clustered at school level.

Table 1.8: Local Gap Parameters of Education Costs

	Coef	SE	Coef	SE
$\lambda_{e,t}(UB)$	1.96	0.325	1.162	0.213
$\lambda_{e,t}(RR)$	1.325	0.256	0.937	0.127
R^2		0.96		0.92

Notes: standard errors are calculated by assuming 2% deviation, the first two colmns are calibrated using 2005's data, while the last two columns are calibrated by 2010's data.

Table 1.9: Regression of Amenities on provincial characteristics in 2005

	(1) Amenities:Urban	(2) Amenities:Rural
House Square Per-Capita	0.205**	0.232**
	(0.08)	(0.09)
Public Expenditure Per-capita	0.003***	0.008***
	(0.00)	(0.00)
log($wateruse$)	5.785*	1.968
	(3.40)	(4.25)
log($pollution$)	-0.038	-0.373
	(0.36)	(0.44)
log($RoadSquare$)	4.657***	6.982***
	(1.28)	(1.48)
log($HealthCarers$)	1.564**	2.481***
	(0.65)	(0.88)
Constant	-45.292**	-60.504**
	(17.61)	(22.37)
N	30	30
R^2	0.6581	0.7903

Notes: Robust standard errors in parentheses, Am_prov is weighted average amenities at at provincial level,Am_ub is weighted average of urban amenities at provincial level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: Summary of Inversion Results

Mean Value of Cost	**2005**				**2010**			
	Skilled		**Unskilled**		**Skilled**		**Unskilled**	
	Rural	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**	**Urban**
Sector Switch Cost								
Industrial	4.88	-6.35	8.14	0.6	2.8	-7.6	6.16	-1.24
Service	1.92	-9.96	9.35	-0.36	1.36	-10.96	7.58	-2.43
Child-Placement Cost								
Migrant	1.81	6.63	2	7.18	0.8	5.6	2.13	7.62
Left-Behind	1.4	8.71	2.08	7.71	-0.24	7.24	1.48	8.16
Education	2.42	1.88	3.34	3.00	1.91	1.37	2.94	2.34
Amenities	-1.57	19.93	-1.59	19.93	-1.58	20.01	-1.64	19.99

Table 1.11: Mean Values of Sector Share

Percentage	AGR(%)	IND(%)	SER(%)
Model			
2005	47.0	21.3	31.6
2010	38.6	24.1	37.3
Data			
2005	50.3	20.7	29.0
2010	37.5	26.7	36.0

Table 1.12: Mean Values of Upward Education Mobility

Pr(HS=1—HS=0)	Migrant	Migrant	Native	Native
Model	Unskilled	Skilled	Unskilled	Skilled
2005	0.45	0.68	0.54	0.75
2010	0.57	0.77	0.65	0.84
Data				
2005	0.4	0.6	0.48	0.68
2010	0.51	0.74	0.59	0.78

Table 1.13: Quantify the Effects of Child-Placement Mechanism

All Moving Together	(1)	(2)	(3)
Δ% National Outcomes	*With Hukou*	*No Educational Mobility*	*Without Hukou*
Welfare	5.69%	-18.12%	5.92%
Welfare:Unskilled	31.59%	10.00%	36.33%
Welfare:Skilled	2.56%	-17.28%	2.24%
Industry(%)	4.49%	0.18%	4.02%
Service(%)	3.38%	-32.56%	4.37%
Urban(%)	8.59%	-23.47%	8.74%
Educational Mobility: Migrant Urban	173.71%	—	411.85%
Educational Mobility: Native Urban	-4.14%	—	-4.74%
Educational Mobility: Native Rural	0.67%	—	2.64%
Theil Index	28.93%	-53.20%	33.72%
Skilled Labor(%)	1.83%	-41.72%	2.86%

Notes: Outcomes are weighted aggregate share of one specific group at the national group. Numbers are the changes in outcomes when all parents moving with children compared with the baseline results to each case. Column(2) shut down the educational mobility channel by setting the probabilities of becoming skilled from unskilled families to 0, Column(3) assumes no hukou threshold.

Table 1.14: Counterfactual Results: National Outcomes

Scenario	**No Hukou Threshold**		**No Migrant Children Cost**		**Lower Net Migrant by 30%***		**Equal Cost***
Δ(%) **in National Outcome**	*Unequal Cost*	*Equal Cost*	*Unequal Cost*	*Equal Cost*	*Unequal Cost*	*Equal Cost*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Welfare	2.91%	21.25%	-6.48%	13.64%	-7.23%	10.28%	-17.95%
Welfare: Unskilled	15.10%	15.06%	23.64%	21.61%	27.11%	26.11%	2.79%
Welfare: Skilled	0.87%	21.56%	-9.97%	12.71%	-11.30%	6.42%	-20.59%
Skilled(%)	2.88%	1.69%	2.25%	0.50%	6.86%	4.09%	3.15%
Industrial Sector Share(%)	1.41%	1.45%	2.84%	3.89%	4.19%	2.77%	-1.30%
Service Sector Share (%)	3.18%	6.32%	3.42%	9.49%	6.19%	11.44%	-5.16%
Urban population(%)	4.23%	10.82%	6.49%	20.43%	9.48%	19.53%	-12.00%
Education Mobility: Urban Migrant	134.06%	69.08%	12.47%	14.35%	108.99%	41.55%	170.50%
Education Mobility: Rural Left-behind	0.29%	0.05%	14.88%	-1.16%	35.27%	15.59%	111.17%
Education Mobility: Urban Native	-0.33%	-0.42%	-0.14%	-0.49%	4.18%	2.71%	0.16%
Education Mobility: Rural Native	0.70%	-0.06%	9.36%	2.20%	40.17%	19.86%	99.55%
Theil Index	22.92%	11.64%	18.98%	64.63%	335.86%	474.77%	-38.31%
Theil Index: Unskilled	28.52%	1.97%	75.50%	60.57%	404.02%	354.29%	-6.64%
Theil Index: Skilled	29.68%	21.63%	19.80%	77.37%	511.49%	554.47%	-40.20%

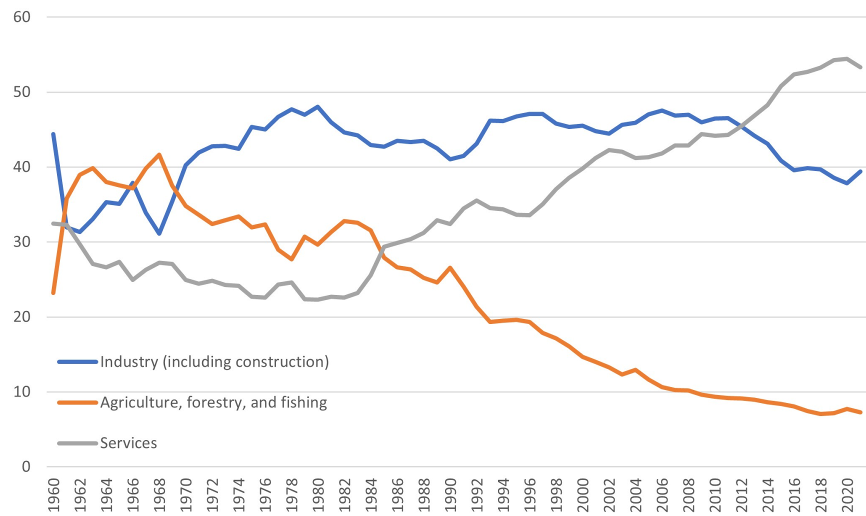
Notes: This table presents the percentage change in weighted average outcomes by population at national level compared to the baselines. Odd columns present the results when educational costs are different across urban and rural, while even columns show the results when the costs are equal. Column(1)-(2) display the results of raising the hukou probability to ones anywhere, Column(3)-(4) display the results of eliminating all migrant children costs, Column(5)-(6) display the results of lowering calibrated migration costs excluding the unvarying costs by 30%, and Column(7) shows the change under equal education costs without migration costs reduction.

Table 1.15: Counterfactual Results: Average Locational Outcomes

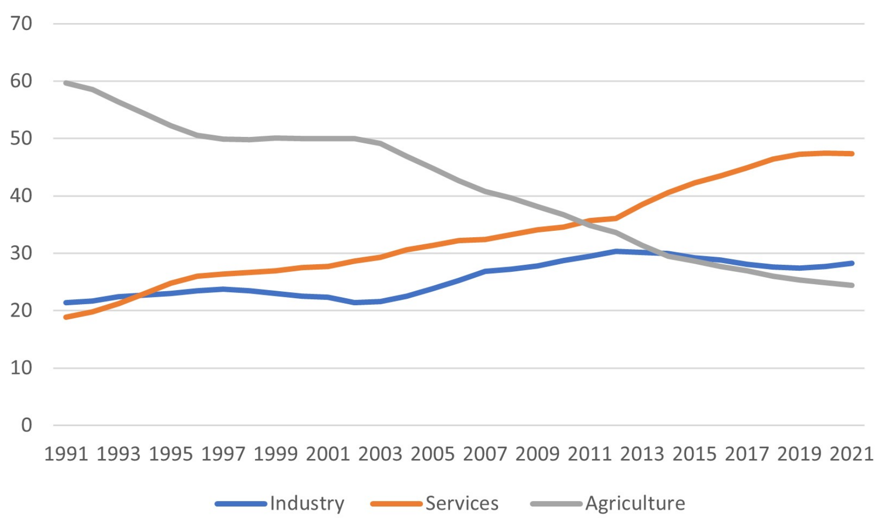
Scenario	**No hukou Threshold**				**No Migrant Children Cost**				**Lower Net Migrant Cost by 30%***			
Δ(%)in Average Locational Outcomes	*East*	*Middle*	*West*	*North-East*	*East*	*Middle*	*West*	*North-East*	*East*	*Middle*	*West*	*North-East*
A: Unequal Educational Cost	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Welfare: Unskilled	0.22%	0.55%	0.11%	-0.14%	0.70%	0.53%	-1.37%	-1.56%	-4.27%	0.85%	-10.13%	-13.41%
Welfare: Skilled	0.38%	0.56%	0.30%	0.24%	2.08%	2.48%	1.41%	1.49%	3.80%	8.65%	4.43%	4.10%
Skilled(%)	4.77%	4.33%	5.28%	9.83%	4.75%	3.92%	3.63%	8.86%	10.29%	11.68%	20.34%	39.68%
Industrial Sector Share(%)	0.61%	-0.44%	2.16%	2.69%	0.40%	1.24%	2.03%	2.02%	4.90%	-8.41%	23.74%	15.53%
Service Sector Share (%)	1.65%	3.26%	2.94%	3.24%	2.03%	2.95%	1.57%	3.43%	5.06%	23.72%	12.55%	18.13%
Urban population(%)	1.50%	2.77%	3.91%	2.61%	-7.25%	3.28%	12.21%	8.13%	6.14%	20.87%	28.41%	17.03%
Education Mobility: Urban Migrant	24.70%	7.57%	19.89%	27.48%	1.23%	2.98%	3.02%	3.71%	10.42%	16.42%	22.44%	27.71%
Education Mobility: Rural Left-behind	0.94%	1.00%	1.08%	2.60%	6.84%	10.50%	13.12%	19.40%	28.18%	33.85%	53.98%	128.12%
Education Mobility: Urban Native	-0.16%	-0.04%	-0.28%	0.00%	0.67%	2.53%	2.37%	2.89%	5.28%	13.79%	17.22%	20.44%
Education Mobility: Rural Native	0.97%	0.93%	1.10%	2.52%	7.34%	10.76%	12.75%	20.91%	30.49%	36.96%	58.00%	130.88%
Theil Index	23.20%	18.21%	21.67%	11.46%	18.93%	33.09%	37.37%	29.25%	436.17%	168.03%	461.79%	197.66%
B: Equal Educational Cost												
Welfare: Unskilled	0.28%	0.54%	0.11%	-0.23%	0.85%	0.40%	-1.46%	-1.84%	-4.03%	1.32%	-9.35%	-12.72%
Welfare: Skilled	0.40%	0.62%	0.32%	0.23%	2.12%	2.47%	1.36%	1.42%	3.86%	8.80%	4.67%	4.25%
Skilled(%)	2.41%	3.94%	5.38%	8.28%	-1.41%	1.84%	3.08%	6.33%	5.50%	10.13%	18.13%	29.78%
Industrial Sector Share(%)	0.00%	-2.42%	3.92%	0.57%	-1.22%	-3.80%	5.91%	-2.33%	2.72%	-9.52%	24.67%	9.70%
Service Sector Share (%)	1.15%	4.65%	2.78%	3.62%	0.83%	6.00%	1.38%	4.56%	3.48%	24.14%	10.92%	16.19%
Urban population(%)	14.95%	3.88%	-2.68%	2.67%	9.14%	8.04%	5.72%	7.22%	23.33%	24.92%	20.01%	15.12%
Education Mobility: Urban Migrant	24.88%	8.00%	19.72%	28.17%	1.38%	3.70%	2.75%	4.57%	10.05%	16.38%	21.52%	27.59%
Education Mobility: Rural Left-behind	0.54%	1.30%	1.41%	2.46%	4.03%	10.26%	14.71%	16.02%	16.49%	30.72%	59.99%	83.32%
Education Mobility: Urban Native	-0.18%	0.24%	-0.46%	0.25%	0.68%	3.15%	2.08%	3.52%	5.06%	13.77%	16.48%	20.46%
Education Mobility: Rural Native	0.56%	1.18%	1.55%	2.08%	4.21%	10.24%	14.50%	16.21%	17.57%	33.57%	64.49%	82.82%
Theil Index	11.98%	10.18%	12.87%	-6.93%	64.93%	35.84%	54.11%	8.01%	470.19%	149.84%	445.75%	142.57%

Notes: This table presents the percentage change in average outcomes compared to the baselines. Panel (A) shows the change compared to the standard baseline with unequal education costs, and Panel (B) is compared to the baseline with equal equation costs. Column(1)-(3) display the results of raising the hukou probability to ones anywhere, Column(5)-(8) display the results of eliminating all migrant children costs, Column(9)-(12) display the results of lowering calibrated migration costs excluding the unvarying costs by 30%. East areas consist: Beijing, Tianjin, Hebei, Shandong, Shanghai,Jiangsu, Zhejiang,Fujian, Guangdong, and Hainan ; Middle areas consist: Shanxi, Anhui, Jiangxi, Henan, Hunan, Hubei; West areas consist: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shannxi, Xizang, Xinjiang, Qinghai, and Gansu; and North-east consists: Liaoning, Jilin, Heilongjiang provinces.

Figure 1.1: Trend of Sector Change



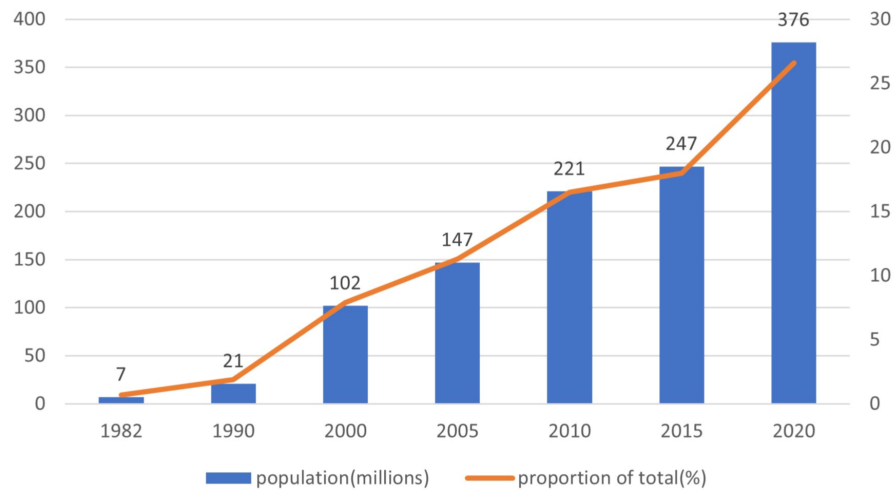
A.GDP Value Added(%):1960-2021



B. Employment Share(%):1991-2021

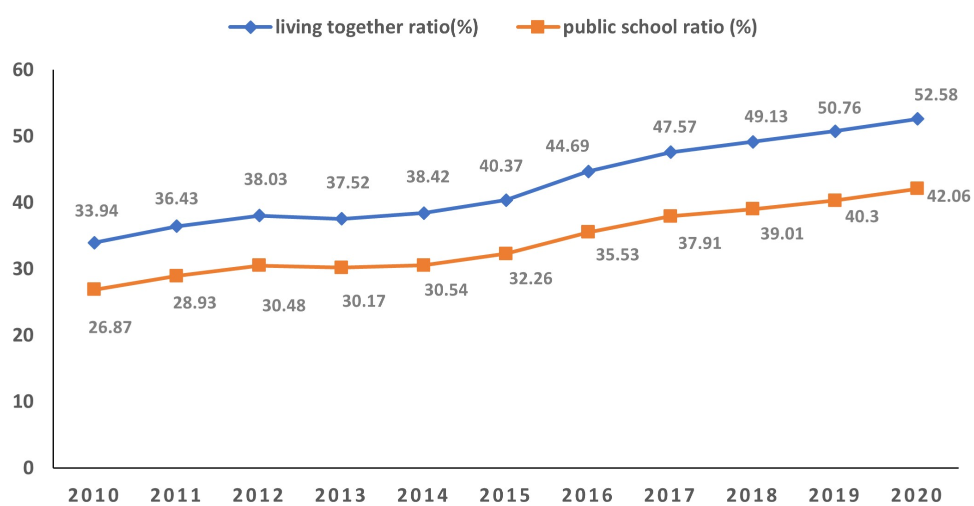
Data Source: World Bank open data.

Figure 1.2: Trend of Migration



Data souce: Chengrong et al. (2022)

Figure 1.3: Status of Children of Migrants aged 6-14: 2010-2020



Data Source: Chinese population census and *the Report of Children in China, 2015.* Living together ratio is calculated using the number of children who live together with their parents of the total children from migrant families, public school ratio is the share of children who enroll in public school of total children from migrant families.

Figure 1.4: Migrants and their Children in China: 2000-2020

Million People	2000	2005	2010	2015	2020
Children of Migrants	49.91	98.64	104.5	103.03	130
migrant children	19.82	25.33	35.81	34.26	71.09
left-behind children(rural)	26.99	58.61	48.27	40.51	34.75
left-behind children(urban)	3.1	14.7	20.42	28.26	24.15

Notes: data from the report of the "Development of children of migrants in China: 2022 ". Left-behind children data in 2020 is estimated based on 2015's ratio.

Figure 1.5: Decision Process

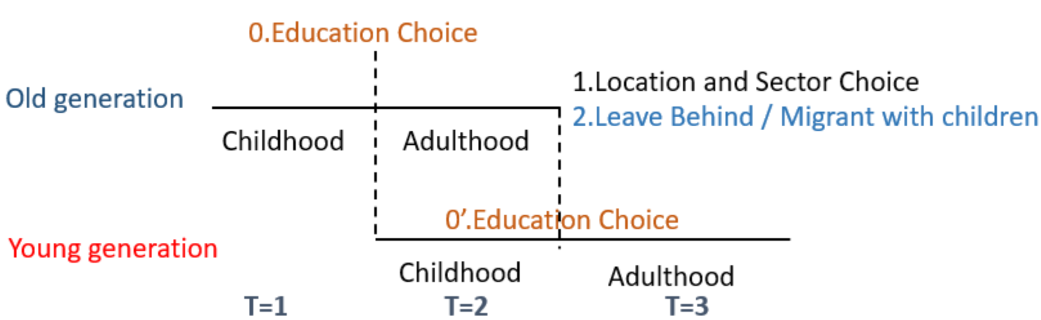
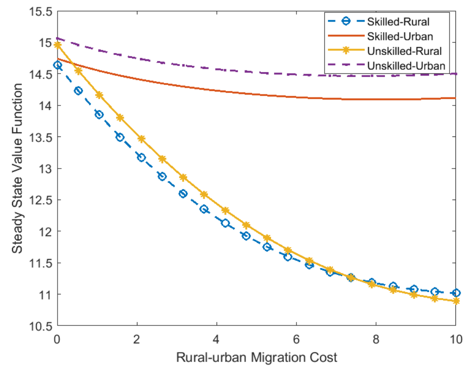
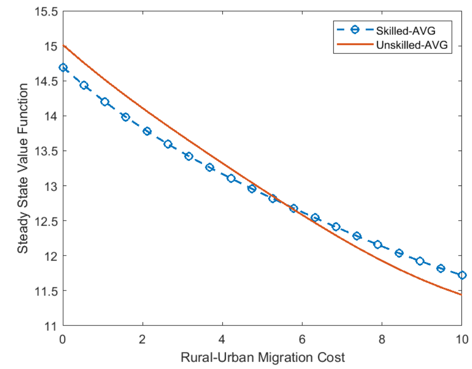


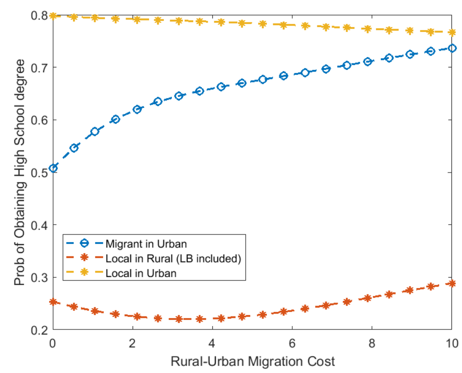
Figure 1.6: Impacts of Rural-Urban Migration Cost: no Migrant Children Cost



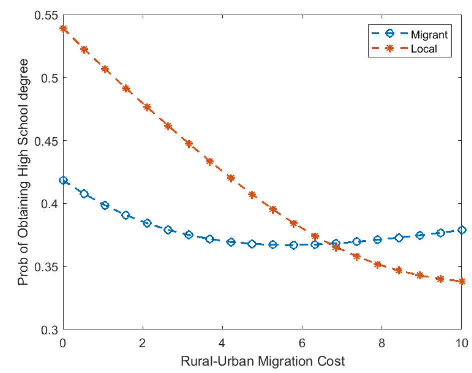
A1.Individual Welfare



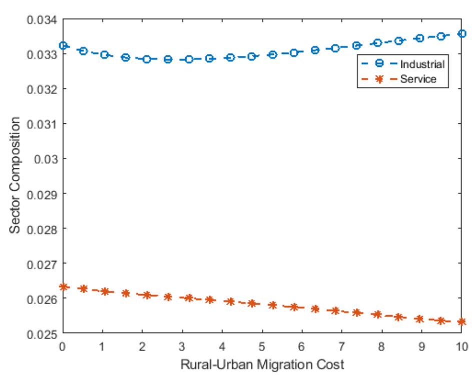
A2.National-Averaged Welfare



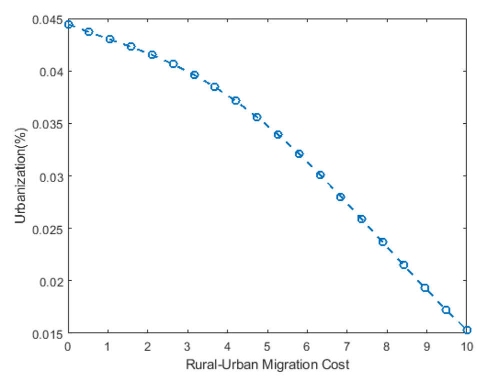
B1.Individual Educational Mobility



B2.National-Averaged Educational Mobility



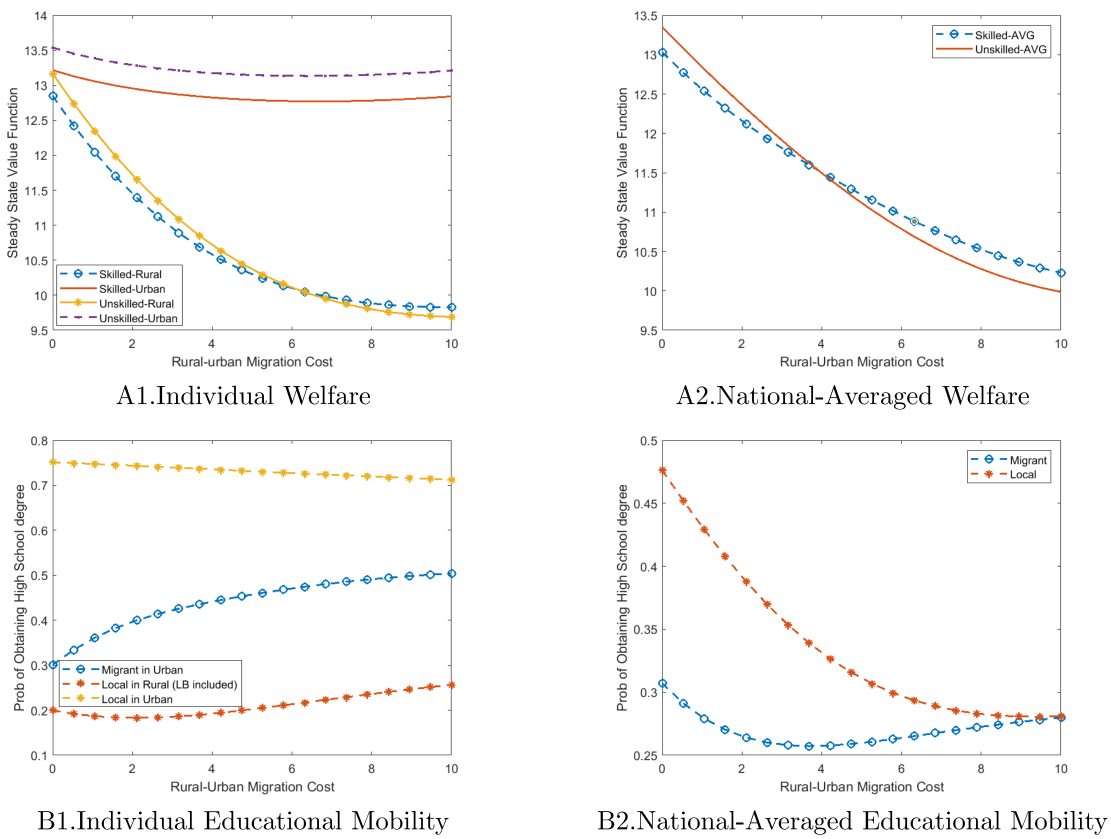
C1.Sector Composition Change



C2.Urbanization Change

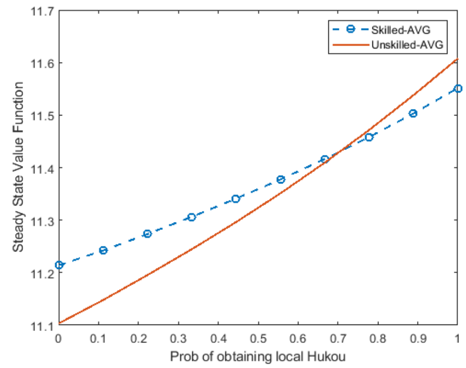
Note: I increase rural-urban migrant cost from 0 to 10, the national weighted average is calculated by $Y = \sum_j s(j)y(j)$, where $s(j)$ is the share of group j in total and $y(j)$ the individual outcome.

Figure 1.7: Impacts of Rural-Urban Migration Cost: with Migrant Children Cost

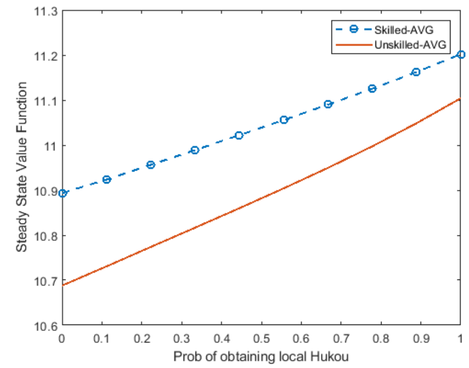


Note: I fix migrant children cost to urban area at 5 while other costs equal 0.

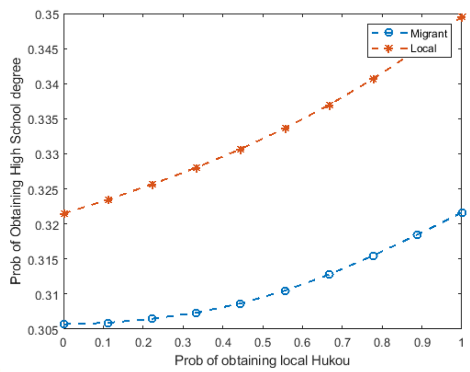
Figure 1.8: Impacts of Rising Hukou Obtaining Probability



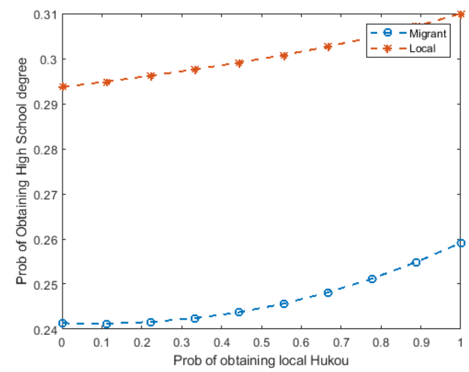
A1. No Migrant Children Cost: Welfare



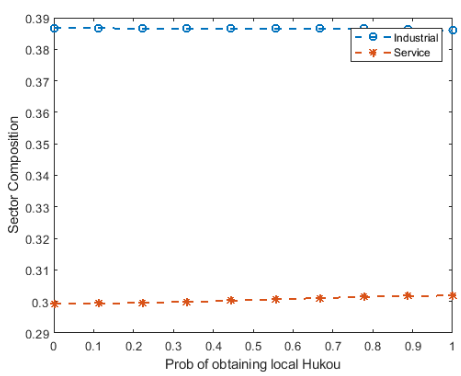
A2. With Migrant Children Cost: Welfare



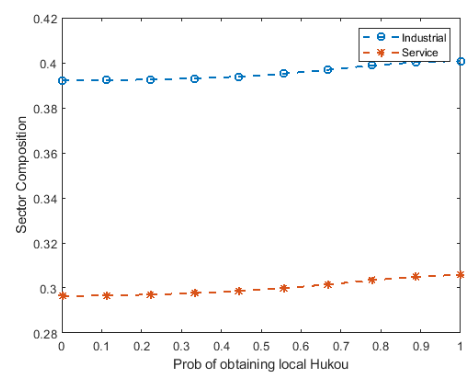
B1. No Migrant Children Cost: Educational Mobility



B2. With Migrant Children Cost: Educational Mobility



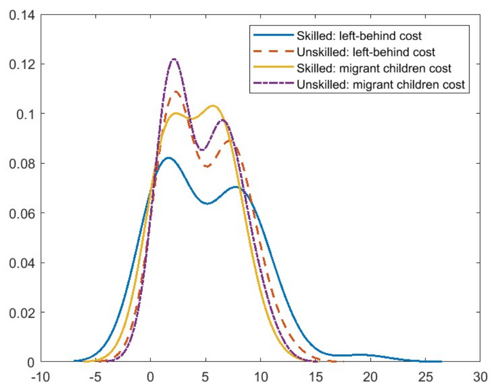
C1. No Migrant Children Cost: Sector Composition



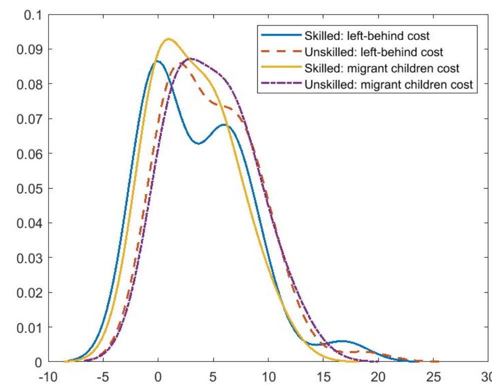
C2. With Migrant Children Cost: Sector Composition

Note: This figure shows the national level weighted-average outcomes where I fix rural-urban migration cost at 5, and increase hukou probability from 0 to 1. Panel(a)(c)(e) show the results without migrant children cost, and Panel(b)(d)(f) show the results with migrant children cost in urban area at 5. The changes in individual outcomes are moderate.

Figure 1.9: Kernel Distribution of children placement costs

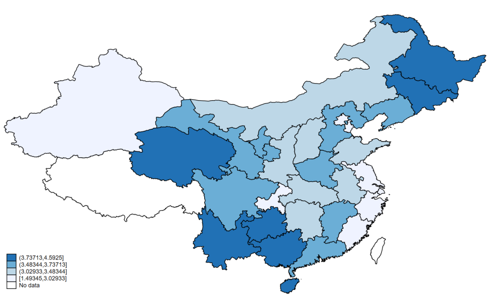


A. Child-placement costs in 2005

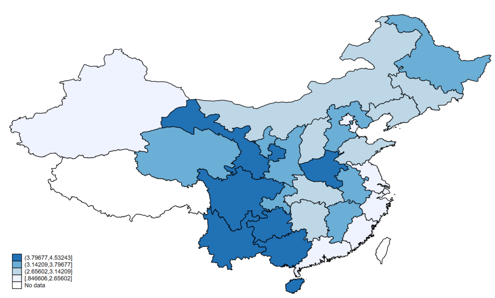


B. Child-placement costs in 2010

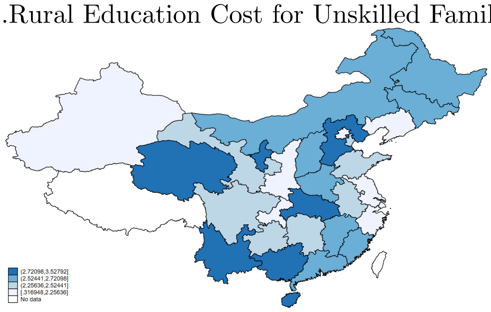
Figure 1.10: Spatial Distribution of Calibrated Exogenous Education Costs in 2005



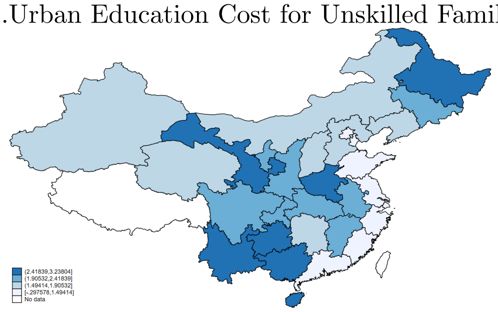
A1.Rural Education Cost for Unskilled Families



A2.Urban Education Cost for Unskilled Families

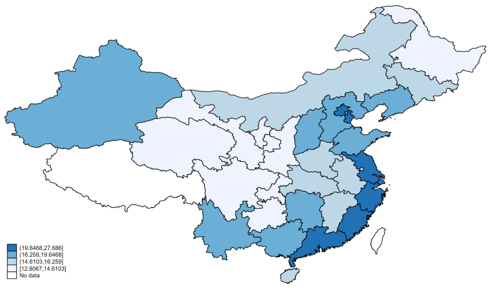


B1.Rural Education Cost for Skilled Families

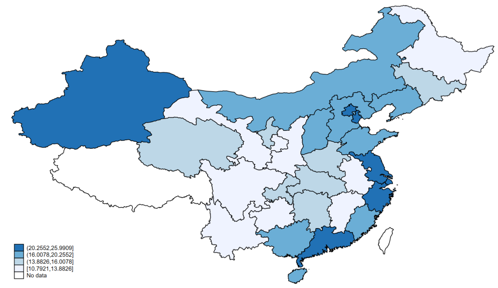


B2.Urban Education Cost for Skilled Families

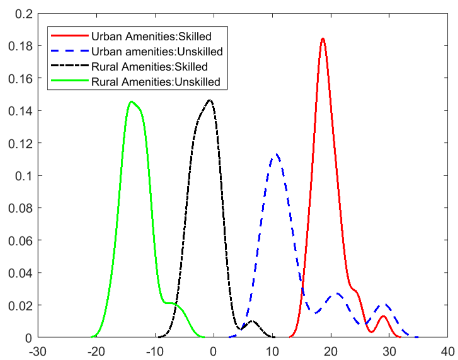
Figure 1.11: Distribution of Urban Amenities



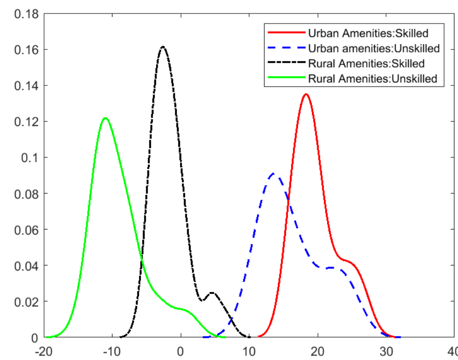
A1. Spatial Distribution in 2005



A2. Spatial Distribution in 2010

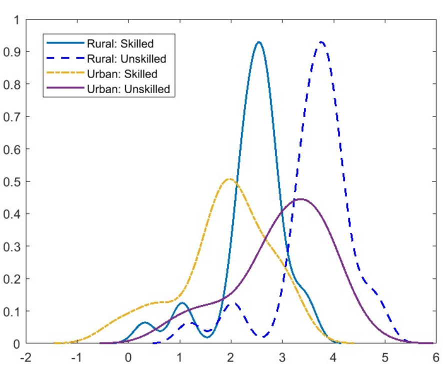


B1.Density Distribution in 2005

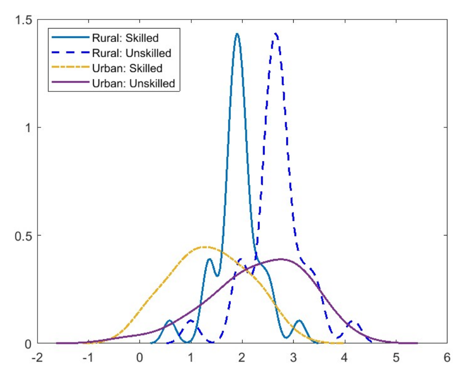


B2.Density Distribution in 2010

Figure 1.12: Kernel Distribution of Calibrated Exogenous Education Costs

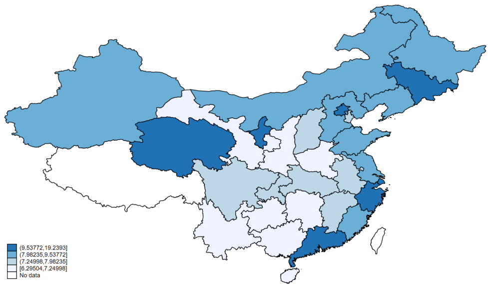


A.Kernel Density Plot in 2005

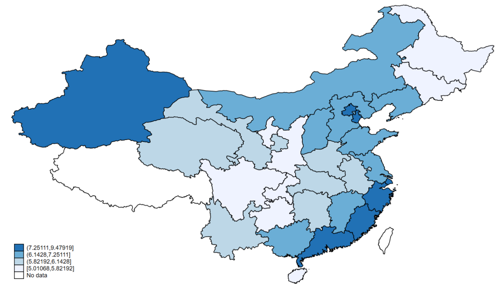


B.Kernel Density Plot in 2010

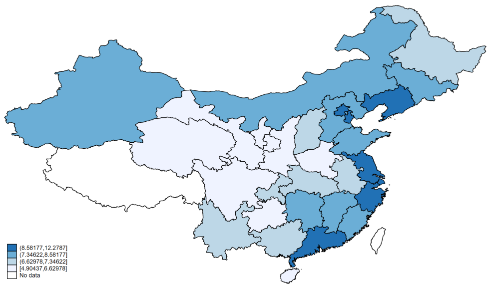
Figure 1.13: Spatial Distribution of Children's Cost in 2005



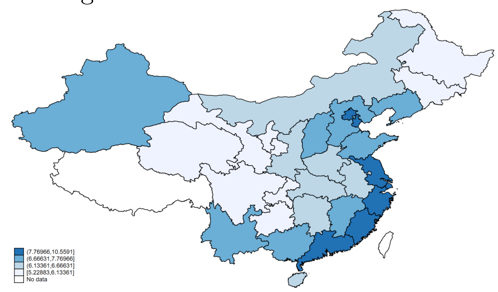
A1.Left-behind Costs for the Skilled



A2.Migrant Children Costs for the Skilled

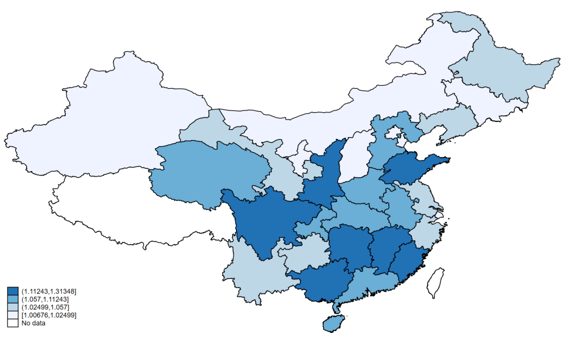


B1.Left-behind Costs for the Unskilled

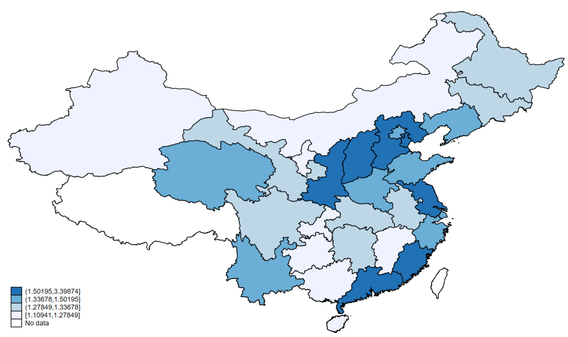


B2.Migrant Children Costs for the Unskilled

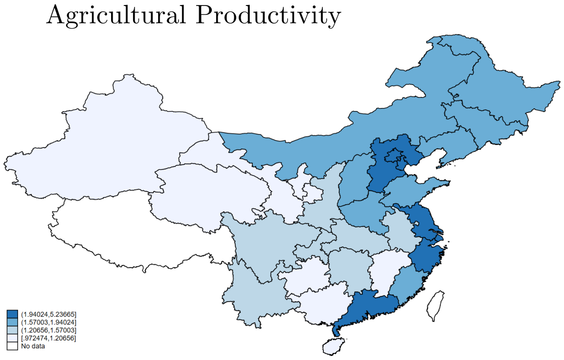
Figure 1.14: Distribution of Productivities in 2005



Agricultural Productivity

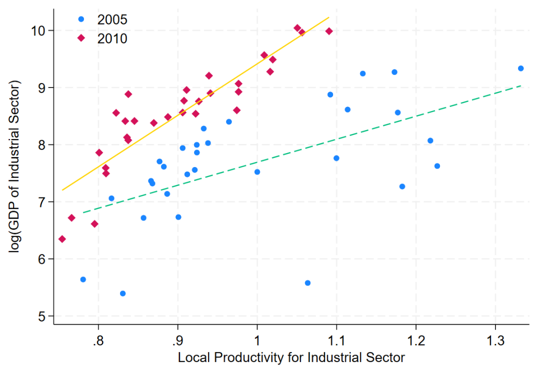


Industrial Productivity

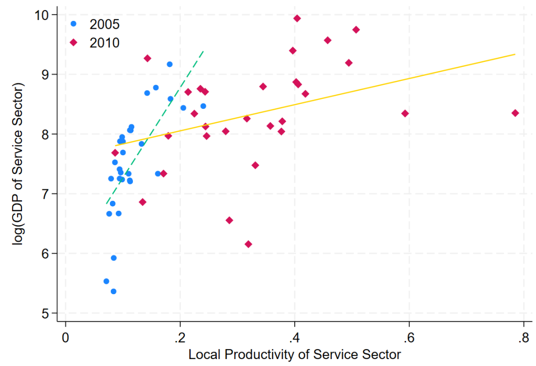


Service Productivity

Figure 1.15: Relationship Between Productivity and GDP for Non-agricultural Sectors

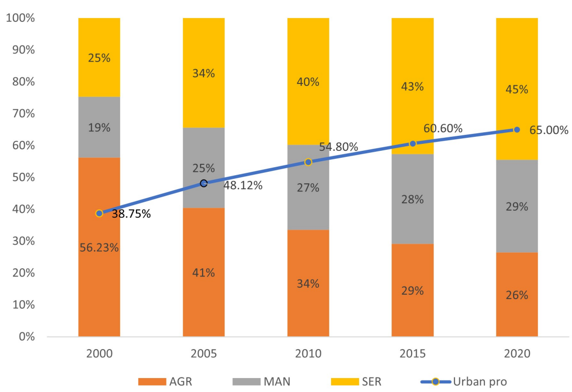


Industrial Sector

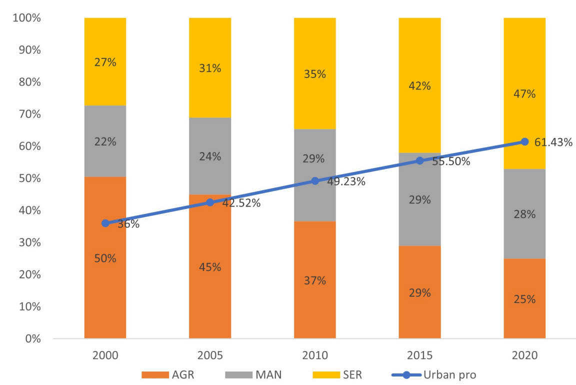


Service Sector

Figure 1.16: Transition Path from 2000-2020



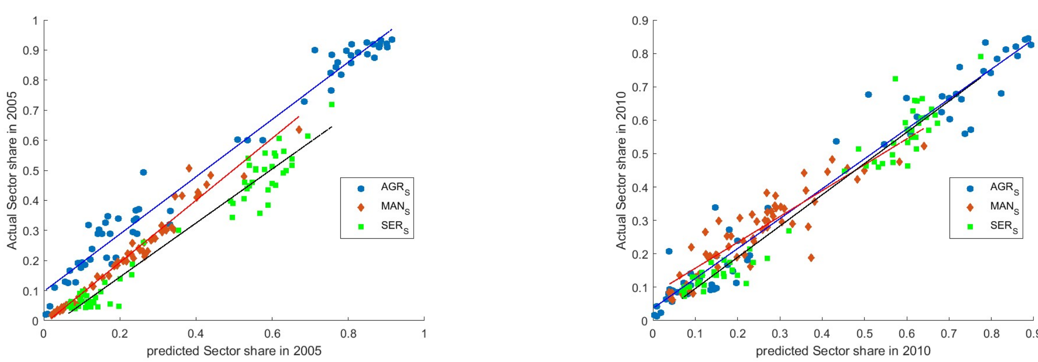
Model



Data

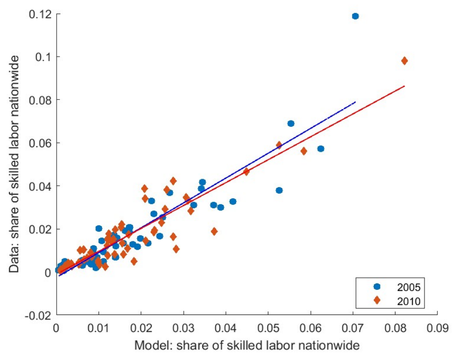
Notes: Here I treat the first period's result as in 2000 due to the discrepancy between micro-census and macro level data, and the subsequent analysis treat them as in 2005.

Figure 1.17: Distribution of Sector Composition across Regions

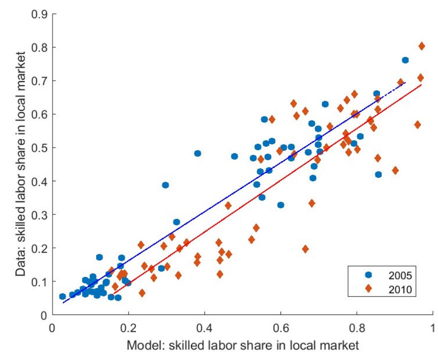


Notes: The left panel shows the distribution in 2005 and the right one shows that in 2010.

Figure 1.18: Distribution of Skill Share across Regions



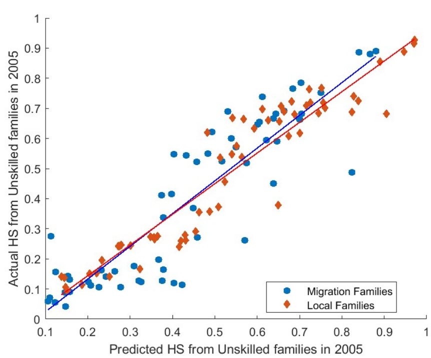
Skilled Share of national skilled labor



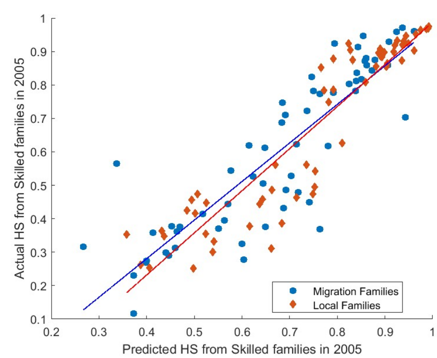
Skilled Share in Local labor market

Notes: This part predicts the young cohorts' education choices, and the counterpart in data is restricted to young people aged 22-28.

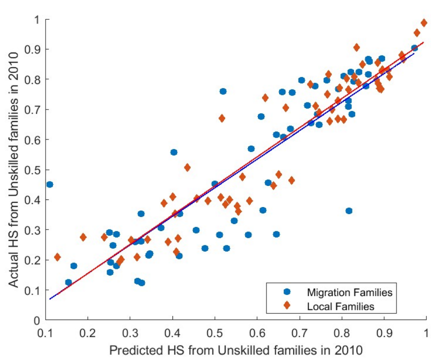
Figure 1.19: Distribution of educational mobility across Regions



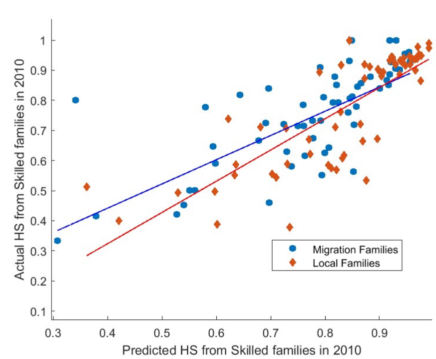
2005: From Unskilled Families



2005: From Skilled Families

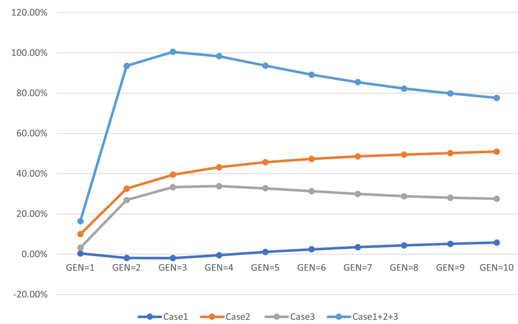


2010:From Unskilled Families

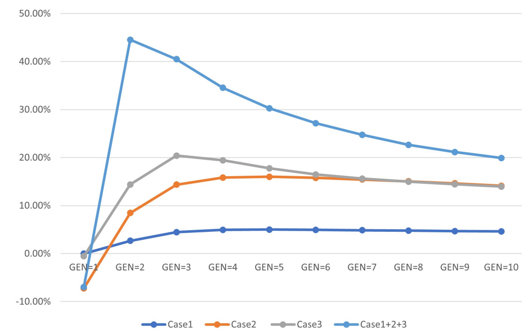


2010:From Skilled Families

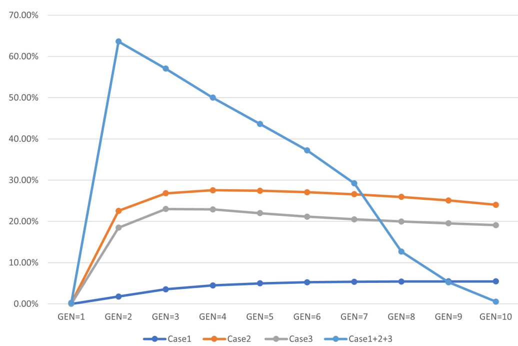
Figure 1.20: Impacts of Migration Costs Reduction on Transition Paths



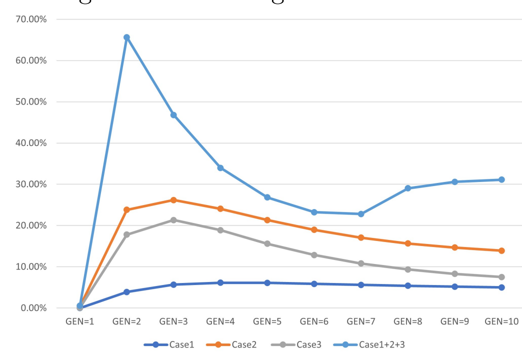
Average Welfare Change for Unskilled Workers



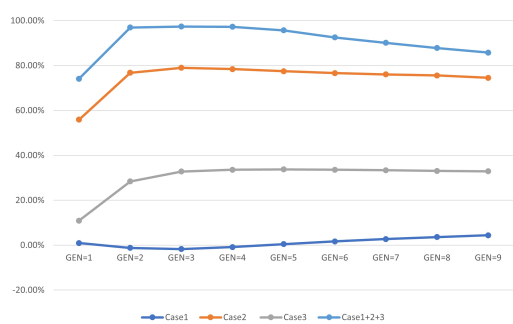
Average Welfare Change for Skilled Workers



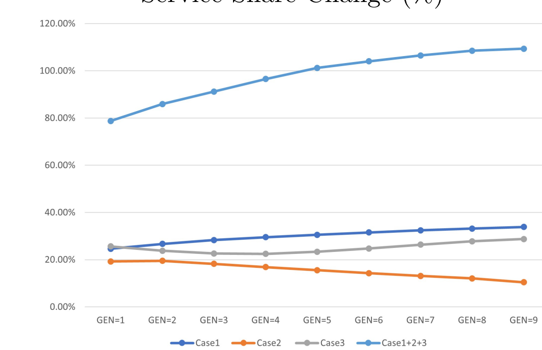
Industrial Share Change (%)



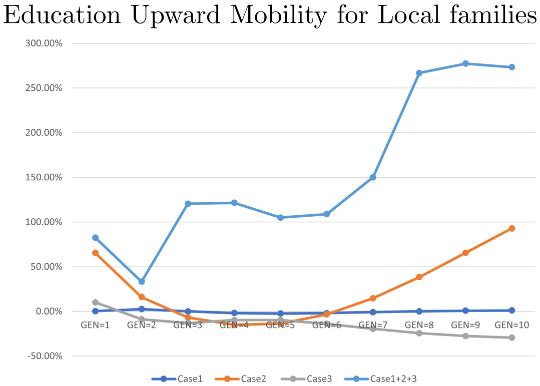
Service Share Change (%)



Education Upward Mobility for Local families



Education Upward Mobility for Migrant families



Theil Index

Notes: All numbers are the percentage change compared to baseline calibration using 2005 mini census, taking 2000's economy as the initial state.The average value of upward education mobility and local workers shares keeps steady across generations, all the others show the aggregate value.

Appendices

1.A Appendix Table and Plots

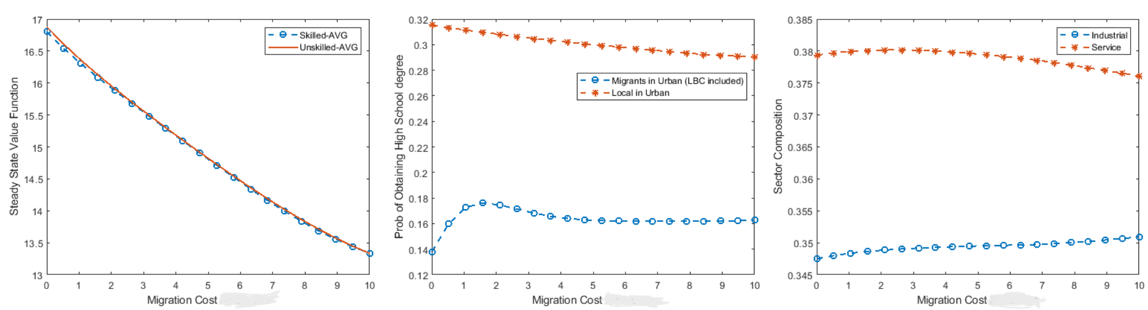
Table 1.A.1: Sector Switching Cost

Switching Cost	p25	p50	p75	Mean	Std
Industrial :2005					
Urban: Unskilled	-1.47	1.77	2.93	0.6	3.73
Rural: Unskilled	6.1	10.11	11.97	8.14	4.97
Urban: Skilled	-8.29	-5.38	-4.66	-6.35	3.36
Rural: Skilled	3.68	6.1	7.9	4.88	4.44
Industrial :2010					
Urban: Unskilled	-2.84	0.06	1.42	-1.24	3.84
Rural: Unskilled	4.27	7.16	9.48	6.16	4.45
Urban: Skilled	-9.3	-7.1	-4.7	-7.6	3.49
Rural: Skilled	1.67	3.66	5.16	2.8	4.41
Service :2005					
Urban: Unskilled	-1.25	-0.1	1.35	-0.36	3
Rural: Unskilled	7.7	10.62	11.75	9.35	3.63
Urban: Skilled	-10.62	-9.52	-8.36	-9.96	2.67
Rural: Skilled	1.23	2.5	3.33	1.92	2.14
Service:2010					
Urban: Unskilled	-3.53	-1.8	-0.78	-2.43	3.11
Rural: Unskilled	6.1	8.6	10	7.58	3.49
Urban: Skilled	-11.88	-10.47	-8.86	-10.96	2.84
Rural: Skilled	0.8	2.23	3.4	1.36	3.08

Table 1.A.2: Left-behind and Migration Children Costs

Child-placement cost	p25	p50	p75	Mean	Std
Left-behind:2005					
Urban: Unskilled	6.63	7.35	8.58	7.71	1.62
Rural: Unskilled	1.68	2.03	2.48	2.08	0.72
Urban: Skilled	7.25	7.98	9.54	8.71	2.48
Rural: Skilled	0.85	1.22	1.6	1.4	0.75
Left-behind: 2010					
Urban: Unskilled	6.41	7.26	9.4	8.16	2.66
Rural: Unskilled	0.9	1.29	1.99	1.48	0.89
Urban: Skilled	5.5	6.48	8.42	7.24	3.1
Rural: Skilled	-0.77	-0.56	0.2	-0.24	0.78
Migration: 2005					
Urban: Unskilled	6.13	6.67	7.77	7.18	1.46
Rural: Unskilled	1.73	2.04	2.32	2	0.58
Urban: Skilled	5.82	6.14	7.25	6.63	1.2
Rural: Skilled	1.17	1.57	2.1	1.81	1.16
Migration together: 2010					
Urban: Unskilled	6.28	6.82	8.96	7.62	1.96
Rural: Unskilled	1.22	1.54	2.33	2.13	2.18
Urban: Skilled	4.27	5.1	7.32	5.6	1.85
Rural: Skilled	-0.42	0.14	0.66	0.8	2.9

Figure 1.A.1: Impacts of Migration Cost With Equal Education Resources



Welfare Change

Educational Mobility

Sector Composition Change

Table 1.A.3: Migration Equation Coefficients

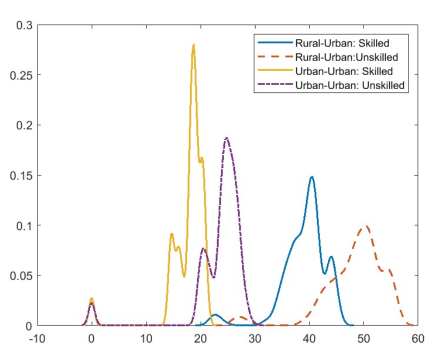
Coef	β_H	β_L	Std_H	Std_L	$pvalue_H$	$pvalue_L$
FromRural						
DZXS	0.000	0.000	0.000	0.000	0.000	0.000
Darea	0.000	0.000	0.000	0.000	1.000	1.000
Dsw*HKStrint	0.007	0.010	0.000	0.000	0.000	0.000
Ddist2	1.666	2.603	0.000	0.000	0.000	0.000
Ddist3	3.880	4.742	0.000	0.000	0.000	0.000
Ddist4	7.665	8.732	0.000	0.000	0.000	0.000
Exp_d	-1.095	-1.782	0.000	0.000	0.000	0.000
Diacdist	0.002	0.003	0.000	0.000	0.000	0.000
Neighbor	-2.313	-2.298	0.000	0.000	0.000	0.000
Dcoast	-4.849	-4.944	0.000	0.000	0.000	0.000
Dswitch	0.132	0.168	0.000	0.000	0.000	0.000
Dsw*DZXS	0.431	0.205	0.000	0.000	0.000	0.000
Dsw*Darea	-2.299	-3.155	0.000	0.000	0.000	0.000
Dsw*Ddist1	5.961	5.060	0.000	0.000	0.000	0.000
Dsw*Ddist2	6.097	5.640	0.000	0.000	0.000	0.000
Dsw*Ddist3	4.614	5.334	0.000	0.000	0.000	0.000
Dsw*Ddist4	4.160	4.886	0.000	0.000	0.000	0.000
Dsw*Diacdist	-0.548	-0.109	0.000	0.000	0.000	0.000
Dsw*NB	0.974	1.276	0.000	0.000	0.000	0.000
Dsw*Dcoast	1.884	1.772	0.000	0.000	0.000	0.000
HKStrint	0.000	0.000	0.000	0.000	0.000	0.000
Dsw*Crossprov	13.647	15.779	0.000	0.000	0.000	0.000
Exp_o	2.359	3.143	0.000	0.018	0.000	0.000
Reform	-0.580	-0.941	0.000	0.001	0.000	0.000
Dsw*Reform	0.175	0.044	0.000	0.000	0.000	0.000
FromUrban						
DZXS	0.000	0.000	0.000	0.000	0.000	0.000
Darea	0.000	0.000	0.000	0.000	1.000	1.000
Dsw*HKStrint	0.160	0.204	0.000	0.000	0.000	0.000
Ddist2	3.593	4.118	0.000	0.000	0.000	0.000
Ddist3	4.320	5.025	0.000	0.000	0.000	0.000
Ddist4	5.793	6.519	0.000	0.000	0.000	0.000
Exp_d	-0.342	0.901	0.000	0.000	0.000	0.000
Diacdist	0.000	0.000	0.000	0.000	0.000	0.000
Neighbor	-1.409	-1.261	0.000	0.000	0.000	0.000
Dcoast	-0.645	-0.156	0.000	0.000	0.000	0.000
Dswitch	-30.628	-31.240	0.000	0.000	0.000	0.000
Dsw*DZXS	3.156	3.353	0.000	0.000	0.000	0.000
Dsw*Darea	-1.295	-1.982	0.000	0.000	0.000	0.000
Dsw*Ddist1	1.392	1.389	0.000	0.000	0.000	0.000
Dsw*Ddist2	-3.108	-2.595	0.000	0.000	0.000	0.000
Dsw*Ddist3	-1.225	-0.834	0.000	0.000	0.000	0.000
Dsw*Ddist4	7.189	7.466	0.000	0.000	0.000	0.000
Dsw*Diacdist	0.355	0.182	0.000	0.000	0.000	0.000
Dsw*NB	-0.886	-0.144	0.000	0.000	0.000	0.000
Dsw*Dcoast	-2.662	-2.185	0.000	0.000	0.000	0.000
HKStrint	0.000	0.000	0.000	0.000	1.000	1.000
Dsw*Crossprov	17.373	18.017	0.000	0.000	0.000	0.000
Exp_o	1.875	2.509	0.000	0.000	0.000	0.000
Reform	0.745	0.801	0.000	0.000	0.000	0.000
Dsw*Reform	0.314	-0.367	0.000	0.000	0.000	0.000
R^2	0.85	0.79				

Table 1.A.4: Regression of Amenities on provincial characteristics in 2005

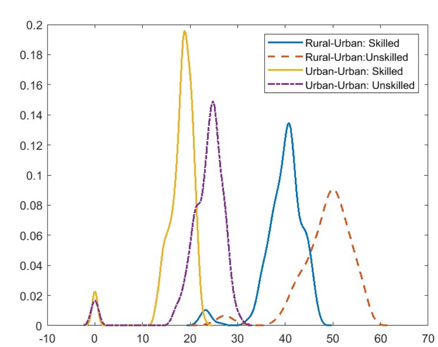
	(1) Amenities:Urban	(2) Amenities:Rural
House Square Per-Capita	0.205**	0.232**
	(0.08)	(0.09)
Public Expenditure Per-capita	0.003***	0.008***
	(0.00)	(0.00)
log($wateruse$)	5.785*	1.968
	(3.40)	(4.25)
log($pollution$)	-0.038	-0.373
	(0.36)	(0.44)
log($RoadSquare$)	4.657***	6.982***
	(1.28)	(1.48)
log($HealthCarers$)	1.564**	2.481***
	(0.65)	(0.88)
Constant	-45.292**	-60.504**
	(17.61)	(22.37)
N	30	30
R^2	0.6581	0.7903

Robust standard errors in parentheses, Am_prov is weighted average amenities at at provincial level,Am_ub is weighted average of urban amenities at provincial level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 1.A.2: Distribution of Calibrated Migration Cost

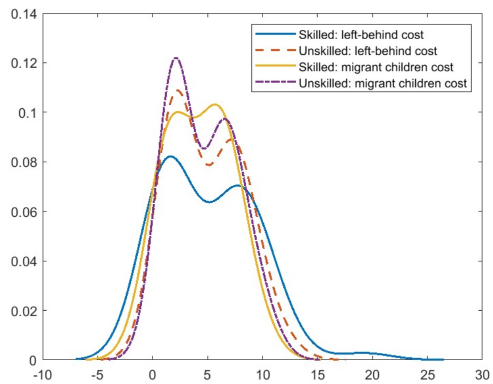


Kernel Density Distribution in 2005

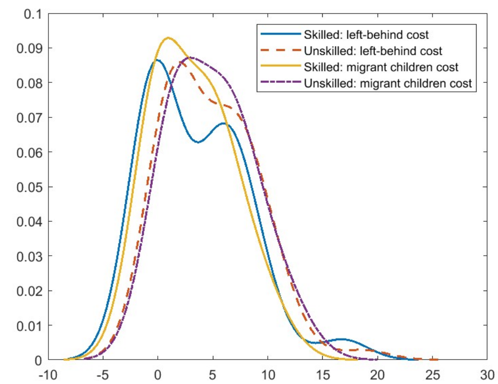


Kernel Density Distribution in 2010

Figure 1.A.3: Kernel Distribution of children placement costs

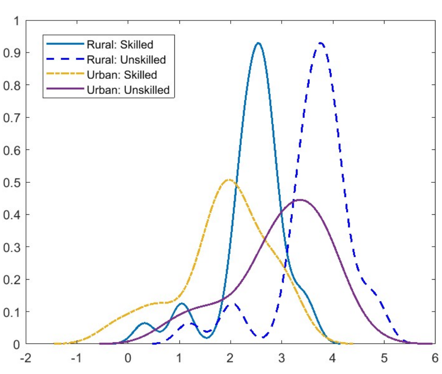


Child-placement costs in 2005

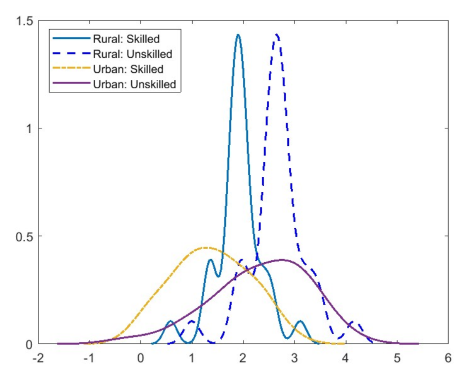


Child-placement costs in 2010

Figure 1.A.4: Kernel Distribution of Calibrated Exogenous Education Costs

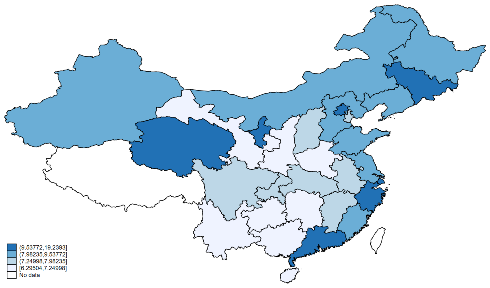


Kernel Density Plot in 2005

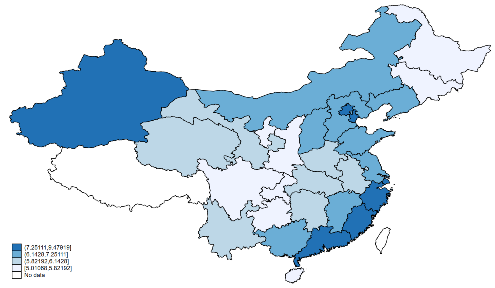


Kernel Density Plot in 2010

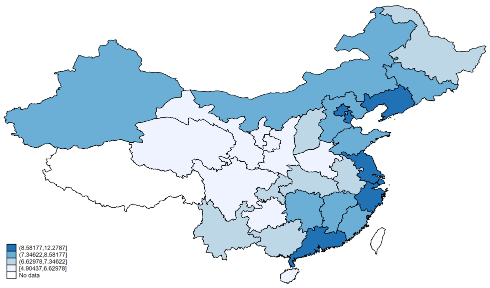
Figure 1.A.5: Spatial Distribution of Children's Cost in 2005



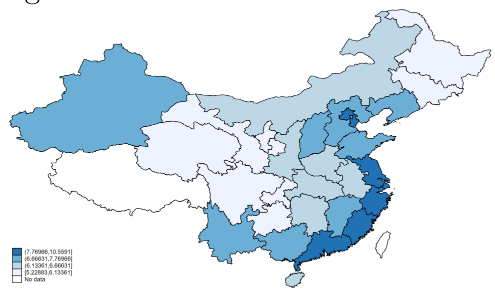
Left-behind Costs for the Skilled



Migrant Children Costs for the Skilled



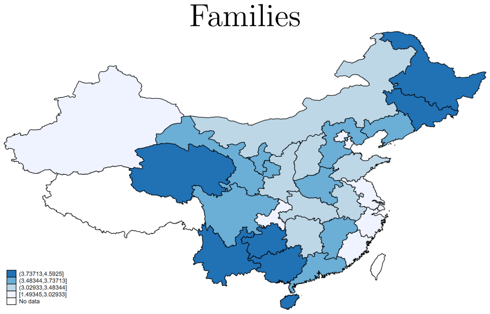
Left-behind Costs for the Unskilled



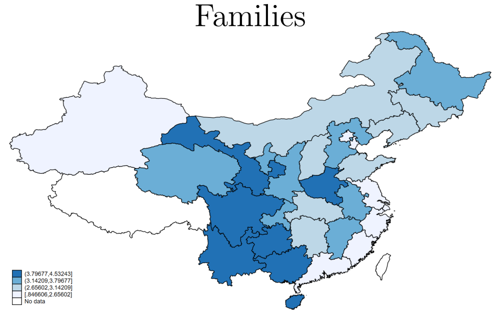
Migrant Children Costs for the Unskilled

Figure 1.A.6: Spatial Distribution of Calibrated Exogenous Education Costs in 2005

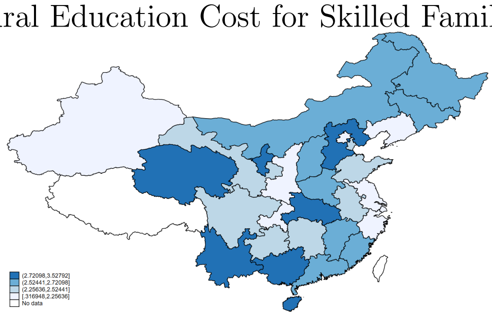
Rural Education Cost for Unskilled Families



Urban Education Cost for Unskilled Families



Rural Education Cost for Skilled Families



Urban Education Cost for Skilled Families

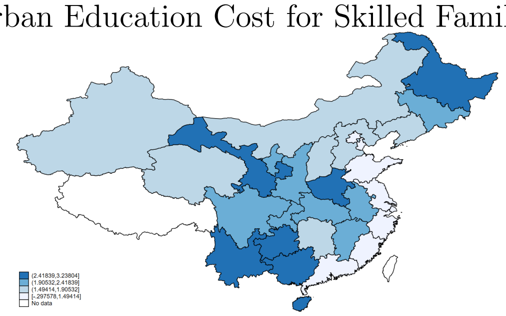


Figure 1.A.7: Distribution of Urban Amenities

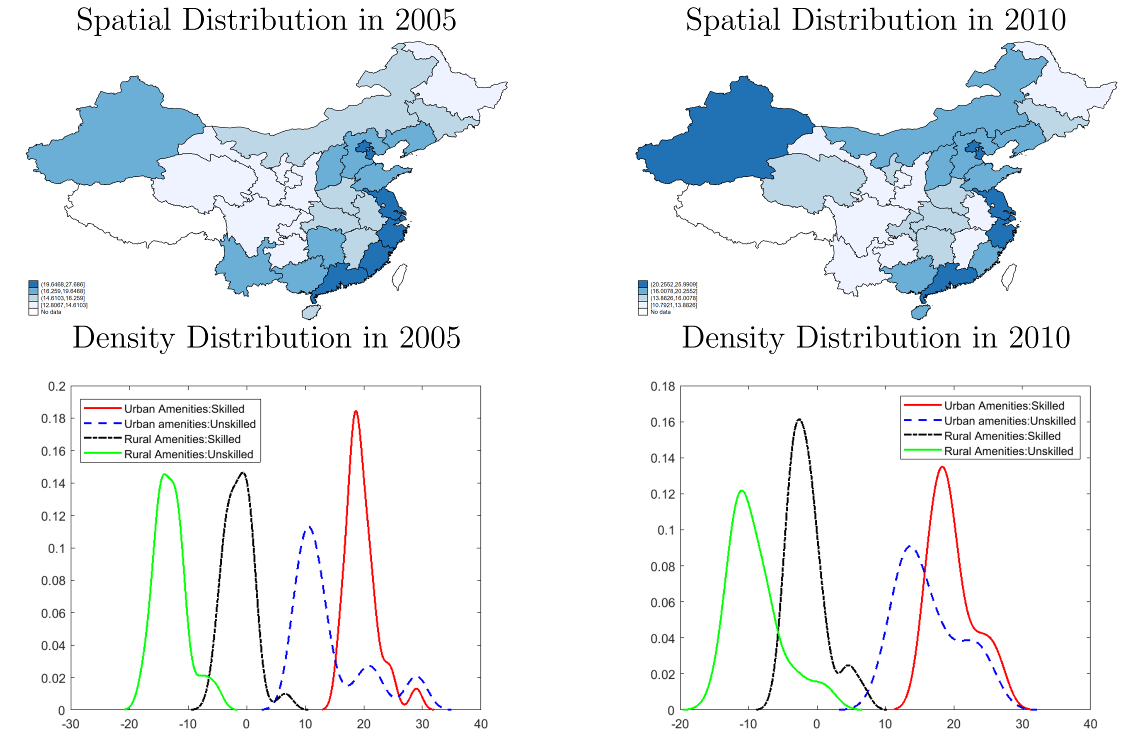


Figure 1.A.8: Distribution of Productivities in 2005

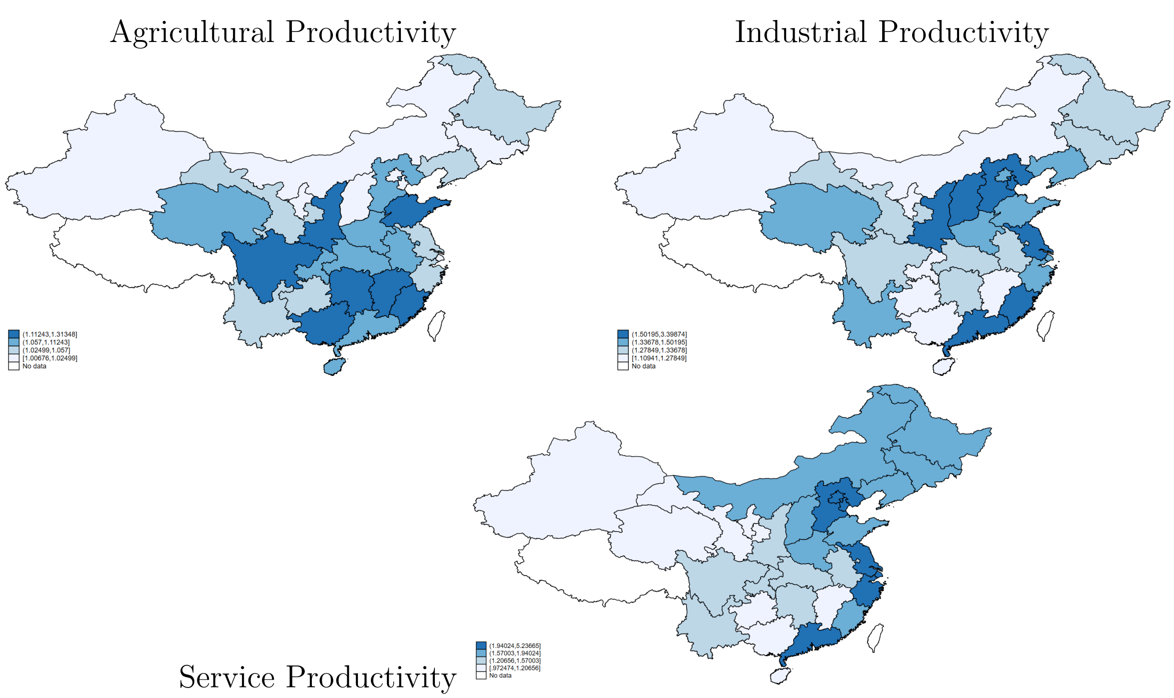
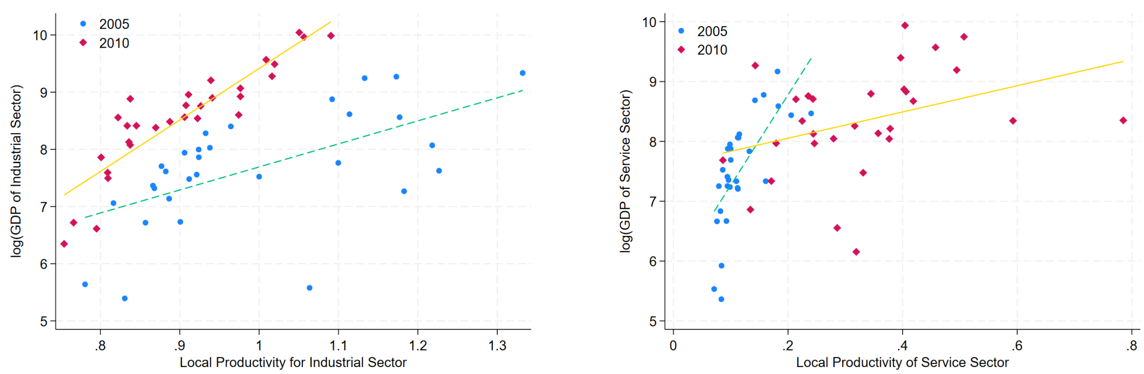


Figure 1.A.9: Relationship Between Productivity and GDP for Non-agricultural Sectors



Industrial Sector　　　　Service Sector

1.B Data

Real Income and Employment

The baseline data I used to calculate the real income and expenditure is 2005 mini population census and 2006 statistical yearbook. Among all the censuses from 2000 to 2015 collected by Chinese government statistics department, the 2005 1% mini population census is the only census that contain income information including the wage, housing rent and value. To calculate the provincial-area level income, I first add up the annual income and house value, then calculate the city-level aggregated revenue from housing rent and distribute them to home owners. I get the expenditure share on education from the 2010 China Family Panel Survey respectively for each area-skill group[30],and then calculate the consumption net of education investment individually. Next, I compute the shares of consumption of each skill-province-area-migration group in total provincial-area consumption, and merge them with the provincial-area consumption data from 2006 Chinese statistical yearbook. Finally I calculate the expenditure at provincial-area-skill-migration level by multiplying the consumption share to the aggregated data from the Chinese Statistical Yearbook (CSY). I can also calculate the real income by deflating the consumption using the price index calculated from independent calibration part in trade. The aggregate employment data at provincial-sector level also comes from the CSY. Then I calculate the employment for each analysis unit using the corresponding employment share computed from 2005 and 2010 census data. Compared with using the data from population census directly, this way of construction enable me to compare the expenditure across times.

Migration Flow

In the empirical part, a migrant worker should satisfy the following requirements:(1) hold agricultural registration type (Hukou) between age 16-60, (2) work in non-agricultural sectors, (3) born in a different town/county. In the quantitative model, I adjust the definition to fit the analysis unit. The migration is defined as the workers who hold agricultural Hukou

[30]Namely, rural-skilled, urban-skilled, rural-unskilled and urban-unskilled.

and live in urban areas and vice versa, or those move from other provinces in the past five years. I then calculate the skilled and unskilled migration flow based on 2005 and 2010 population census.

High School Attainment Ratio

I first distinguish the workers and students for young people aged 16-19[31], and then separately compute the probability of attaining at least high school degree for them from different families, which is defined by (1) whether the highest education of their parents is at least high school (skilled family or not); (2) whether neither of his parents is migrant. For the people still at school, I compute the share of the young people who attain at least high school degree at their living province-area. For those who are already in the labor market, the share is computed at their original province 5 years ago and Hukou property instead, considering the possibility that they receive education at their original province and area.

Migrant and Left-behind Children Matrix Once the parent decide to migrate, he/she need to decide whether to bring her/his children with him. The question of "the number of survival children" offers the information of the number of children of females members in the household. I calculate the number of migrant and left-behind children follow the steps: first, I restrict the sample to the parents who marry after 1985 and above age 18 to make sure their children are below 20. Then I match the child-parent pair according to their household ID, and get the number of children for each pair. Identifying the migrate children as those who live with their parents, and the number of left-behind children can be calculated by subtracting the number of migrant children from the number of total children. Similar as the migration flow, I construct the flow of left-behind and migrant children at origin-destination level for each element of the migration matrix.

[31] The reason for using this specific age range is twofolded: first, the human capital index calculated based on CEPS data focus on children aged between 13-15 and the age range 16-19 is the closest age range that reflect the impact of this human capital index. Second, I can find the information of their parents more easily than other age range, as people are more likely to leave their family when they become older. The census ask the reviewers to report their education level regardless of their schooling status, so the education level won't be affected for those who are still at school. I also try other age ranges like 16-22, 18-25, and the results are similar.

Imputation for Individual Wage In this part, I use data and model structure to estimate parameters and obtain the fundamentals of the real economy. The model is mapped into the Chinese economy. The basic analysis unit is 30 province5, and sector are classified as Agriculture and Non-agriculture, and all sectors are tradable. Data on employment ,wage and income come from censuses and statistic yearbooks. 2005mini census is the only year that cover individual's wage and asset information, I calculate the shares of each cell and map them to the data from statistical yearbook. For 2010, 2015 and 2020, I take the following steps to impute the wage and income:

1. Use Urban Household Survey data (2009 for 2010) to estimate the skill premium coefficient using Mincer equation with additional individual controls:

$$\ln W_{ijt} = \beta_j Skill_{ijt} + \Gamma X_{ijt} + \gamma_{ct} + \epsilon_{it}$$

Here j denotes the industry i works in which belongs to one of the 20 broad industries, c denotes the city i lives. The regression is run separately for each industry so I get 20 β_j.

2. I get the city-industry specific average wage $\bar{w}_{dj}$ from city statistic yearbook and fill the missing wages by provincial-industry average wage from the national statistic yearbook.Note that the wage only contains workers in urban areas.

3. Supplemented with known labor allocation from census data, I first calculate the urban-rural average wage rate R and using the following equation to recover rural and urban average city industry wage respectively:

$$w_{dj}(i \in \{UB, RR\}) = \bar{w}_{dj} \frac{Emp_r + Emp_u}{REmp_r + Emp_u}$$

Then the city-industry-skill specific wage for urban and rural areas can be recovered similarly:

$$w^L_{dj}(i \in \{UB, RR\}) = w_{dj}(i \in \{UB, RR\}) \frac{H_l + L_l}{e^\beta H_l + L_l}, w^H_{dj}(i \in \{UB, RR\}) = e^\beta w^l_{dj}(i \in \{UB, RR\})$$

4.After recover wage data, I use the provincial-level wage to income rate for urban citizens from statistic yearbooks to recover the income level. However, the yearbook don't publish such data for rural areas, so I borrow that number from CFPS report and assume the it's the same across the country. Then I calculate the corresponding shares of each city-industry-skill cell in total provincial income, and multiply them with the rural and urban income data from the yearbook.

1.C Proofs and Propositions

1.C.1 Aggregation Property of PIGL Utility

Using Roy's identity, I can get the demand for good in sector n for individuals working in (d, j) as:

$$x_{dj}^{g}(n) = -\frac{\partial u_{dj}(g)/\partial P_{dn}}{\partial u_{dj}(g)/\partial e_{dj}(g)} = \frac{e_{dj}^{g}\alpha\omega_n}{P_{dn}} - \gamma_n \frac{\mathbb{P}_{dj}(\frac{e_{dj}^{g}}{\mathbb{P}_{dj}})^{1-\epsilon}}{P_{dn}} \tag{1.23}$$

so the expenditure share on the good n for people in (d,j) is

$$\phi_{dj}^{g}(n) = \frac{x_{dj}^{g}(n)P_{dn}}{e_{dj}^{g}(n)} = \alpha\omega_n + \gamma_n(\frac{e_{dj}^{g}}{\mathbb{P}_{dj,g}})^{-\epsilon} \tag{1.24}$$

where $\mathbb{P}_{dj,g} = (P_{dF}^{\omega_F} P_{dG}^{\omega_G} P_{dS}^{\omega_S})^{\alpha}(r_{dj})^{1-\alpha}$ is the price index for people in (d,j) with migration status g. When computing the equilibrium, I rescale the expenditure share to the range $(0, 1)$ if it is negative or larger than 1. Utilizing the aggregation property of PIGL preference, I can get the aggregate expenditure share on good n for people in (d,j) and d:

$$\tilde{e}_{dj} = [\sum_{s}\sum_{q} e_{dj}(s,q)^{-\epsilon}\omega_{dj}(s,q)]^{-\frac{1}{\epsilon}} = [\sum_{s}\sum_{q} e_{dj}^{s}(q))^{-\epsilon}\omega_{dj}(s,q)]^{-\frac{1}{\epsilon}} \tag{1.25}$$

$$\tilde{e}_{d} = [\sum_{s}\sum_{q}\sum_{j} e_{dj}(s,q)^{-\epsilon}\omega_{dj}(s,q)]^{-\frac{1}{\epsilon}} = [\sum_{s}\sum_{q}\sum_{j} e_{dj}^{s}(q))^{-\epsilon}\omega_{dj}(s,q)]^{-\frac{1}{\epsilon}} \tag{1.26}$$

Therefore the total expenditure share for sectors $n \in \{F, G, S\}$ expressed in average consumption in (d,j) and d are:

$$\Phi_{dj}^{n} = \alpha\omega_n + \gamma_n[\frac{\tilde{e}_{dj}}{(P_{dF}^{\omega_F} P_{dG}^{\omega_G} P_{dS}^{\omega_S})^{\alpha}(r_{dj})^{1-\alpha}}]^{-\epsilon} \tag{1.27}$$

$$\Phi_{d}^{n} = \alpha\omega_n + \gamma_n[\frac{\bar{e}_{d}}{(P_{dF}^{\omega_F} P_{dG}^{\omega_G} P_{dS}^{\omega_S})^{\alpha}(\bar{r}_{d})^{1-\alpha}}]^{-\epsilon} \tag{1.28}$$

where $\bar{r}_d$ is the local average land rent which can be expressed in terms of $\bar{e}_d$,weighed average of consumption and r_{dj}:

$$\bar{r}_d = \sum_j r_{dj} \left(\frac{\sum_s \sum_q e_{dj}(s,q)^{-\epsilon} \omega_{dj}(s,q)}{\bar{c}_d^{-\epsilon}} \right)^{\frac{1}{(1-\alpha)\epsilon}}$$

The other way to express the expenditure share using the inequality term $\phi = (\frac{\tilde{e}(i)}{\bar{e}(i))})^{-\epsilon}$:[32]:

$$\Phi_{dj}^{n} = \alpha\omega_n + \gamma_n \phi[\frac{\bar{e}_{dj}}{(P_{dF}^{\omega_F} P_{dG}^{\omega_G} P_{dS}^{\omega_S})^{\alpha}(r_{dj})^{1-\alpha}}]^{-\epsilon} \tag{1.29}$$

1.C.2 Local Premium

The premium rebate only for local workers δ_{dj} is defined as:[33]

$$\bar{e}_{dj}^{g} L_{dj}^{g} = w_{dj}^{g} L_{dj}^{g} + (\delta_{dj} - 1) w_{dj}^{g} L_{dj}^{g}(n = loc) = w_{dj}^{g} L_{dj}^{g}(1 + (\delta_{dj} - 1)\frac{L_{dj}^{g}(n = loc)}{L_{dj}^{g}}) \tag{1.30}$$

Therefore, plugging in equation(1.30) the expression for total income is:

$$\bar{e}_{dj} L_{dj} = \frac{R_d^j}{\alpha} = \sum_s w_{dj}^{g} L_{dj}^{g}(1 + (\delta_{dj} - 1) m_{loc,g}^{g}) \tag{1.31}$$

[32]Here I assume the term is constant across time and region, and aggregating from individual level to (d,j,s,q) level uses the same technique With $\phi = 0.67$.

[33]Note that the d is at the provincial level, From here I can express the average nominal income for workers in cell (d,j,g) as an equation of $m(loc, g) = \frac{L_{dj}^{g}(n=loc)}{L_{dj}^{g}}$ is :

$$\bar{c}_{dj}^{g} = w_{dj}^{g}[1 + (\frac{1}{\alpha\beta_l^j} - 1)\frac{m(loc,g)}{(1-\eta_{dj}^{L})m(loc,L) + \eta_{dj}^{L} m(loc,H)}]$$

which is useful to impute the 2000 and 2010 real earnings.

Finally we can get the expression for local-premium as a function of local share $m^g_{dd,j}$, total wage bill and expenditure share. In the model I assume people choose sector after choosing the location, so the migration share is the same across each sector:[34]

$$\delta_{dj} = \frac{\frac{\sum_g w^g_{dj} L^g_{dj}}{\alpha\beta^l} - \sum_g w^g_{dj} L^g_{dj}}{\sum_g w^g_{dj} L^g_{dj} m^g_{dd,j}} + 1 \tag{1.32}$$

As $\frac{1}{\alpha\beta^j_l} - 1 > 0$, $\delta_{dj} > 1$ always holds.

1.C.3 Existence and Uniqueness of the Equilibrium at the Steady State

Proposition 1. In the steady state, if $0 < B < \sigma^s_z < \sigma_g < 1$ holds, then the value function has a unique solution which can be computed iteratively applying Pervo Fixed Point Theorem.

Proof: To get the sub-condition of the convergence of value function, I take the utility at d $\bar{u}_d(g)$ and amenities $\tilde{B}$ as given. First, I transform the expected value for children with family moving from o to d with group g to the following expression:

$$o(od, g) = \sum_{l \in \{o,d\}} \left[\sum_{g'} \left(\sum_d \bar{u}_d(g')^{\frac{1}{\sigma^{g'}_z}} \tilde{b}^{g'}_d{}^{\frac{1}{\sigma_g}} c^{g'}_{od}{}^{-\frac{1}{\sigma_g}} o(od, g')^{\frac{\beta}{\sigma^g_z}} \right)^{\frac{\sigma^{g'}_z}{\sigma_g}} \times I(g' = H) z_d(g)^{-\frac{1}{\sigma_g}} \right]^{\sigma_g} \tilde{t}^g(l|STATUS)^{-1} \tag{1.33}$$

where $o(od, g) = exp(\mathcal{O}(od, g))$, $\bar{u}_d(g) = exp(\bar{U}_d(g)), c^f_{od} = exp(C^g_{od}), z_d(g) = exp(z_d(g))$, and $\tilde{t}^g(l|STATUS) = exp(t^g(l|STATUS))$ denotes the transformed carrying or leaving behind costs for children depend on his status. The equation can be expressed in the general form of $x_{oc} = \sum_{d=1}^N f_{odc}(x_{d1}, ...x_{dc})$ in 's paper, where f_{odc} is the function that governs the

[34] The migration matrix is sparse if assuming the migration decision were made after sector choice. Another limitation is that I fix the rural-urban wage gap for each sector at each province to be a constant which calculated from 2005 mini census to get the province-area level wage.

impact that an interaction with location d has o's equilibrium outcome of type c (here c is multi-leveled that includes the leave-or-take and skill group). This set of equations form a 2N-by-2N (n denote region) partitioned matrix, with the N-by-N submatrice for each skill group lies on the diagonal. Since all elements and interaction function f_{odc} are strictly positive, I define the elasticity $\epsilon_{odc,dc'} = \frac{\partial \ln f_{odc}(x_d)}{\partial \ln x_{dc'}}$ and $A_{cc'} = sup_{od}(|\frac{\partial \{ln f_{odc}}{\partial \ln x_{dc'}}|)$ as the uniform bounds of the elasticities where $|\epsilon_{odc,dc'}(x_d)| \leq (A)_{cc'}$, then there exists a unique solution to this equation if the spectral radius of matrix A (i.e, the largest eigenvalue in absolute value) $\rho(A) < 1$. Thereby I can get the three conditions $\sigma_z^s < 1$, $\frac{\sigma_z^s}{\sigma_g} < 1$, $\frac{B}{\sigma_z^s} < 1$, and combine them together come to the first proposition. This condition indicates that the altruistic parameter should be small enough to guarantee the convergence of the value function, and the location taste should not be too different, at least smaller than the education taste.

Proposition 2. Consider an economy in the steady state with log-utility function, i.e, $u = log(\frac{w}{\mathbb{P}})$, where $\mathbb{P}_{dj} = r_{dj}^{1-\sum_j \omega_j} \prod P_{dj}^{\omega_j}$ is the price index at d for people in j with fixed expenditure share. . A sufficient condition for the existence of a unique steady-state spatial distribution of economic activity (up to a choice of units) given time-invariant locational fundamentals and costs is that the spectral radius of a coefficient matrix (A) of model parameters $\{\omega_j, \eta, B, \sigma_z, \sigma_g, \rho, \beta_j^l, \gamma_T, \xi_j, \theta\}$ is less than or equal to 1.

Proof: The equation system can be partitioned into three parts: (1) good market clear and sector choice; (2) value function; (3) population flow. In sum there are 14 endogenous variables with 14 equations in the system. [35] For the first part, $\{\bar{u}_d(g), P_{dj}, W_{dj}, E_{dj}, w_{dj}^g, L_{dj}^g\}$ are the six endogenous variables of equations of local utility (1.34),price index(1.35), good

[35]First I transform all variables to its exponential form for convenience.

market clearing(1.36), composite labor and wage equations(1.37):

$$\bar{u}_d(g)^{\frac{1}{\eta}} = \sum_j w_{dj}^{g\ \frac{1}{\eta}} (r_{dj}^{1-\sum_j \omega_j} \prod_h (P_{dh})^{\omega_h} m_d^g(j))^{-\frac{1}{\eta}} \tag{1.34}$$

$$P_{dj}^{-\theta} = Const \sum_{o=1}^{L} \tilde{\tau}_{od}^{j\ -\theta} (E_{dj})^{\gamma_j^T} W_{oj}^{-\beta_j^l \theta} r_{oj,h}^{-\theta \beta_h^j} \tag{1.35}$$

$$W_{oj}^{\beta_j^l \theta + 1} E_{oj}^{1-\theta\gamma_j^T} r_{oj}^{\theta \beta_j^h} = \omega_j \beta_j^l \sum_{d=1}^{L} \sum_{h \in J} P_{dj}^{\theta} \tilde{\tau}_{od,j}^{-\theta} \frac{W_{dh} E_{dh}}{\beta_h} \tag{1.36}$$

$$W_{dj} = \sum_{g \in \{H,L\}} \lambda_{dj} w_{dj}^{g\ 1-\rho}, \quad E_{dj} = \sum_{g \in \{H,L\}} \lambda_{dj}^{\frac{1}{\rho}} L_{dj}^{g\ \frac{\rho-1}{\rho}} \tag{1.37}$$

The value function conditions consist three equations following each individual decision step with three endogenous variables $\{v(o,g), o(od,g), o(o,g)\}$:

$$v(o,g)^{\frac{1}{\sigma_z}} = \sum_d (\bar{u}_d(g) \tilde{b}_d^g)^{\frac{1}{\sigma_z}} L_{dj}^{\frac{\xi}{\sigma_z}} c_{od}^{g\ -\frac{1}{\sigma_z}} o(od,g)^{\frac{\beta}{\sigma_z}} \tag{1.38}$$

$$o(od,g) = \sum_{l \in \{o,d\}, c \in \{MG, LB\}} o(l,g) \tilde{t}^g(l|c)^{-1} \tag{1.39}$$

$$o(o,g)^{\frac{1}{\sigma_g}} = \sum_{g' \in \{H,L\}} v(o,g')^{\frac{1}{\sigma_g}} I(g' = H) z_o(g)^{-\frac{1}{\sigma_g}} \tag{1.40}$$

Finally, the population flow include six equations with five endogenous variables corresponding to the aggregate individuals of different education choices, children migration status and sector allocation $\{L_d^g, F(d,g), G(d,g), K(d,g,MIG), K(d,g,LB)\}$, the last equation helps pin down $\{w_{dj}^g, L_{dj}^g\}$:

$$L_{d'}^{g'} = \sum_d F(d,g') \left(\frac{\bar{u}_{d'}(g')\tilde{b}_{d'}(g)}{v(d,g)c_{od}^g} \right)^{\frac{1}{\sigma_z}} L_d^{\frac{\xi}{\sigma_z}} o(dd',g')^{\frac{B}{\sigma_z}}$$

$$F(d,g') = \sum_{g\in\{H,L\}} \left(\frac{v(d,g)}{o(o,g)z_d(g)I(g'=H)} \right)^{\frac{1}{\sigma_z}} G(d,g)$$

$$G(d,g)o(d,g)^{-1} = \sum_{l\in\{o,d\},c\in\{MG,LB\}} K(d,g,c)$$

$$K(d,g,B)L_d^{g-1}v(d,g)^{\frac{1}{\sigma_z}} t^g(d|LB) = \sum_l o(dl,g)^{\frac{B}{\sigma_g}-1}(\bar{u}_l^g\tilde{b}_d(g))^{\frac{1}{\sigma_z}} L_d^{\frac{\xi}{\sigma_z}}$$

$$K(d,g,MG)\tilde{t}^g(d|MG)(\bar{u}_d^g\bar{b}_d^g)^{-\frac{1}{\sigma_z}} L_d^{-\frac{\xi}{\sigma_z}} = \sum_o o(od,g)^{\frac{B}{\sigma_h g}-1} c_{od}^{g\,-\frac{1}{\sigma_z}} v(o,g)^{-\frac{1}{\sigma_g}} L_o^g$$

$$L_{dj}^g w_{dj}^{g\,-\frac{1}{\eta}} = L_d^g(\bar{u}_d^g r_{dj}^{1-\sum_j \omega_j} \prod_h (P_{dh})^{\omega_h} m_d^g(j))^{-\frac{1}{\eta}}$$

Following Allen, Arkolakis and Li (2020)'s strategy and pull them into one system, I express the elasticities of left-hand side of the equations in a matrix Λ, and those of the right hand side in a matrix Γ, which are both 14-by-14 matrices. Let $A \equiv \|\Gamma\Lambda^1\|$ and denote the spectral radius (eigenvalue with the largest absolute value) of this matrix by $\rho(A)$. From Theorem 1 in Allen, Arkolakis and Li (2020), a sufficient condition for the existence of a unique equilibrium (up to a choice of units) is $\rho(A) \leq 1$.

Bibliography

Allen, Treb, and Dave Donaldson. 2020. "Persistence and path dependence in the spatial economy." National Bureau of Economic Research.

Allen, Treb, Costas Arkolakis, and Xiangliang Li. 2020. "On the equilibrium properties of network models with heterogeneous agents." National Bureau of Economic Research.

Attanasio, Orazio, Sarah Cattan, Emla Fitzsimons, Costas Meghir, and Marta Rubio-Codina. 2020. "Estimating the production function for human capital: results from a randomized controlled trial in Colombia." *American Economic Review*, 110(1): 48–85.

Cao, Huoqing, Chaoran Chen, Xican Xi, and Sharon Xuejing Zuo. 2023. "Family Migration and Structural Transformation." *Available at SSRN 4559073*.

Caselli, Francesco, and Wilbur John Coleman II. 2001. "The US structural transformation and regional convergence: A reinterpretation." *Journal of political Economy*, 109(3): 584–616.

Caucutt, Elizabeth M, and Lance Lochner. 2020. "Early and late human capital investments, borrowing constraints, and the family." *Journal of Political Economy*, 128(3): 1065–1147.

Chengrong, Duan, Qiu Yuding, Huang Fan, and Xie Donghong. 2022. "From 6.57 Million to 376 Million: Remarks on Migration Transition in China." *Population Research*, 46(6): 41.

Chen, Xilu, Guangyu Pei, Zheng Michael Song, and Fabrizio Zilibotti. 2022. "Tertiarization Like China." National Bureau of Economic Research.

Chen, Yuanyuan, and Shuaizhang Feng. 2019. "The education of migrant children in China's urban public elementary schools: Evidence from Shanghai." *China Economic Review*, 54: 390–402.

Chetty, Raj, and Nathaniel Hendren. 2018. "The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects." *The Quarterly Journal of Economics*, 133(3): 1107–1162.

Chetty, Raj, Nathaniel Hendren, and Lawrence F Katz. 2016. "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment." *American Economic Review*, 106(4): 855–902.

Démurger, Sylvie. 2015. "Migration and families left behind." *IZA World of Labor*.

Dong, Yiming, and Charlotte Goodburn. 2020. "Residence permits and points systems: New forms of educational and social stratification in urban China." *Journal of Contemporary China*, 29(125): 647–666.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, geography, and trade." *Econometrica*, 70(5): 1741–1779.

Eckert, Fabian, and Michael Peters. 2022. "Spatial structural change." National Bureau of Economic Research.

Eckert, Fabian, and Tatjana Kleineberg. 2021. "Saving the American dream? Education policies in spatial general equilibrium." *Education Policies in Spatial General Equilibrium (March 9, 2021).*

Fan, Jingting. 2019. "Internal geography, labor mobility, and the distributional impacts of trade." *American Economic Journal: Macroeconomics*, 11(3): 252–88.

Fan, Tianyu, Michael Peters, and Fabrizio Zilibotti. 2023. "Growing Like India—the Unequal Effects of Service-Led Growth." *Econometrica*, 91(4): 1457–1494.

Galle, Simon, Andrés Rodríguez-Clare, and Moises Yi. 2023. "Slicing the pie: Quantifying the aggregate and distributional effects of trade." *The Review of Economic Studies*, 90(1): 331–375.

Garriga, Carlos, Aaron Hedlund, Yang Tang, and Ping Wang. 2023. "Rural-urban migration, structural transformation, and housing markets in China." *American Economic Journal: Macroeconomics*, 15(2): 413–440.

Hao, Tongtong, Ruiqi Sun, Trevor Tombe, and Xiaodong Zhu. 2020. "The effect of migration policy on growth, structural change, and regional inequality in China." *Journal of Monetary Economics*, 113: 112–134.

Heckman, James J. 1976. "Estimates of a human capital production function embedded in a life-cycle model of labor supply." In *Household production and consumption.* 225–264. NBER.

Herrendorf, Berthold, and Todd Schoellman. 2018. "Wages, human capital, and barriers to structural transformation." *American Economic Journal: Macroeconomics*, 10(2): 1–23.

Hsu, Wen-Tai, and Lin Ma. 2021. "Urbanization policy and economic development: A quantitative analysis of China's differential hukou reforms." *Regional Science and Urban Economics*, 91: 103639.

Huang, Zibin. 2022. "Peer Effects, Parental Migration and Children's Human Capital: A Spatial Equilibrium Analysis in China." *Parental Migration and Children's Human Capital: A Spatial Equilibrium Analysis in China (September 5, 2022).*

Imbert, Clément, Joan Monras, Marlon Seror, and Yanos Zylberberg. 2023. "Floating population: migration with (out) family and the spatial distribution of economic activity." Federal Reserve Bank of San Francisco.

Katz, Lawrence F, and Kevin M Murphy. 1992. "Changes in relative wages, 1963–1987: supply and demand factors." *The quarterly journal of economics*, 107(1): 35–78.

Khanna, Gaurav, Wenquan Liang, Ahmed Mushfiq Mobarak, and Ran Song. 2021. "The productivity consequences of pollution-induced migration in China." National Bureau of Economic Research.

Liang, Zai, Zhongshan Yue, Yuanfei Li, Qiao Li, and Aihua Zhou. 2020. "Choices or constraints: Education of migrant children in urban China." *Population Research and Policy Review*, 39: 671–690.

Liao, Pei-Ju, Ping Wang, Yin-Chi Wang, and Chong Kee Yip. 2020. "To stay or to migrate? When Becker meets Harris-Todaro." National Bureau of Economic Research.

Li, Xiaofan. 2022. "Migration, Regional Education Quality andWelfare Inequality." *The Journal of World Economy*, , (45(07)).

Oster, Emily. 2019. "Unobservable selection and coefficient stability: Theory and evidence." *Journal of Business & Economic Statistics*, 37(2): 187–204.

Porzio, Tommaso, Federico Rossi, and Gabriella Santangelo. 2022. "The human side of structural transformation." *American Economic Review*, 112(8): 2774–2814.

Shu Xu, Ru Wang, Jingying Hu Jipeng Zhang. 2023. "Moving together or Leaving Behind: the impact of School Enrollment Policy on the children of Rural Migrants." *Working Paper*.

Sieg, Holger, Chamna Yoon, and Jipeng Zhang. 2023. "The Impact of Local Fiscal and Migration Policies on Human Capital Accumulation and Inequality in China." *International Economic Review*, 64(1): 57–93.

Song, Xi, Catherine G Massey, Karen A Rolf, Joseph P Ferrie, Jonathan L Rothbaum, and Yu Xie. 2020. "Long-term decline in intergenerational mobility in the United States since the 1850s." *Proceedings of the National Academy of Sciences*, 117(1): 251–258.

Takeda, Kohei. 2022. "The Geography of Structural Transformation: Effects on Inequality and Mobility." Working Paper.

Tombe, Trevor, and Xiaodong Zhu. 2019. "Trade, migration, and productivity: A quantitative analysis of china." *American Economic Review*, 109(5): 1843–72.

Valencia Caicedo, Felipe. 2018. "The Mission: Human Capital Transmission, Economic Persistence, and Culture in South America*." *The Quarterly Journal of Economics*, 134(1): 507–556.

Wu, Wenbin, and Wei You. 2023. "Should Governments Promote or Slow the Pace of Urbanization? A Quantitative Analysis of the Internal Migration Restrictions in China." *Available at SSRN 3637557.*

Yuanyuan Chen, FU Wei. 2023. "Migration Control Policy in Megalopolis,School Enrollment Requirement and Children Left-behind." *China Economic Quarterly*, 23: 91–107.

Zárate, Román D. 2022. *Spatial misallocation, informality, and transit improvements: Evidence from mexico city.* The World Bank.

Chapter 2

Impacts of Trade Liberalization on Educational Mobility

2.1 Introduction

The long-term effects of trade liberalization have garnered increasing attention in academia (e.g., Bastos and Santos, 2022; Dix-Carneiro and Kovak, 2017; Furceri et al., 2022; Grieco, Li and Zhang, 2019; Kim, Lin and Suen, 2010; Lou and Li, 2022; Shahbaz, 2012). Given that these effects may amplify over time (Bastos and Santos, 2022; Dix-Carneiro and Kovak, 2017), understanding the long-term impact is crucial for policymakers and society. While previous literature has primarily focused on economic growth (e.g., Furceri et al., 2022; Grieco, Li and Zhang, 2019; Shahbaz, 2012) and labor market dynamics (e.g., Bastos and Santos, 2022; Dix-Carneiro and Kovak, 2017), limited attention has been paid to intergenerational mobility, with notable exceptions including Ahsan and Chatterjee, 2017, Lou and Li, 2022, and Mitra, Pham and Ural Marchand, 2022.

Intergenerational mobility is intimately linked to equality and social welfare (Chetty et al., 2014; Fan, Yi and Zhang, 2021). Among several determinants, education and human capital accumulation of subsequent generations are critical for intergenerational mobility (Heckman and Mosso, 2014). This paper aims to investigate the causal relationship between trade liberalization and intergenerational education mobility, contributing to our understanding of how trade liberalization affects long-term social equity.

Trade liberalization impacts the opportunity cost of education by creating new job opportunities and altering the skill mix in local labor markets, which in turn affects the skill premium (Atkin, 2016; Li, 2018; Lin and Long, 2020). An increase in demand for low-skilled jobs may raise the opportunity cost of education, encouraging young people to enter the labor market rather than pursue further education (Atkin, 2016). Conversely, if trade liberalization induces technological upgrading and increased competition among firms, the skill premium may rise, incentivizing young people to attain higher levels of education (Li, 2020).

Furthermore, trade liberalization indirectly affects the educational outcomes of the next generation by influencing parents' labor market conditions, an aspect that has received less attention in previous literature. If trade liberalization increases family income (Cheng and Potlogea, 2017), the income effect may boost investment in children's education (Jacoby and Skoufias, 1997; Jensen, 2000). However, if parents take advantage of new job opportunities in expanding tradable sectors, they may spend less time interacting with their children, potentially negatively impacting educational outcomes (Chang, Dong and MacPhail, 2011; Zhang et al., 2014; Zhao et al., 2014).[1]

This study distinguishes itself from previous literature by examining the impact of both direct and indirect channels on the educational outcomes of future generations resulting from trade liberalization. We explore how these effects vary according to parents' education levels, conducting separate empirical analyses for families with high levels of education (where at least one parent has obtained education beyond high school) and families with low levels of education (where neither parent has achieved a high school diploma). China's accession to the World Trade Organization (WTO) in 2001 provides an ideal setting to study the impact of international trade on intergenerational education mobility. We leverage regional variations

[1]For instance, Facchini et al. (2019) find that trade liberalization induces substantial internal migration flows in China.

in exposure to trade shock, determined by pre-accession regional industry structure and exogenous industry-level shocks, to examine the effect of trade liberalization on educational outcomes (Brandt et al., 2017; Dix-Carneiro and Kovak, 2017; Erten and Leight, 2021; Kovak, 2013, among others). This shift-share approach offers several advantages. First, it captures the heterogeneous exposure to trade liberalization across regions, reflecting the fact that areas with different industrial compositions experienced varying degrees of shock. Second, by using pre-accession employment shares, we mitigate concerns about endogenous changes in industrial structure in response to trade liberalization. Third, the instrument's reliance on industry-level tariff changes, which are plausibly exogenous to local economic conditions, strengthens our identification strategy.

To capture temporal variation, we identify youth whose school years coincided with the trade shock as the treatment group, while older cohorts serve as the control group. We then employ a cohort Difference-in-Differences (DID) specification to analyze the effect of trade liberalization on educational outcomes. This approach allows us to exploit both spatial and temporal variations in exposure to trade liberalization, enhancing the robustness of our causal inference and helping to isolate the impact of trade liberalization from other concurrent economic changes.

We utilize multiple waves of population census data from 2000, 2005, 2010 and 2015 for the main analysis,[2] and other data sources such as the Urban Household Survey (UHS), China Family Panel Survey (CFPS), and China Household Income Project (CHIP) to investigate the mechanisms behind our findings.

Several novel findings stand out. First, export tariff reduction decreases education for individuals from low-educated families while imposing insignificant impacts on those from highly-educated families. One concern is that the one-child policy implemented in 1980s may confound the estimates, so we control for the number of children of the same parents in the basic regression. Several robustness checks also confirm that the result is robust and

[2]For 2005 and 2015, we use the so-called "mini census" data, i.e., the 1% population survey data, which is a survey on a randomly-selected 1% sample of the population.

causal. For example, we use the spatial variation of trade shocks based on one's registration city instead of residence city to address the issue that someone had migrated after receiving education. We include the city-level change in the proportion of college enrollment in the period of 2000 to 2005 to address the issue that college expansion that occurred in 1999 may affect education choice and bias our results. We also conduct Oster tests to validate that our results are unlikely to be explained by unobserved omitted variables. These results suggest that trade liberalization reduces intergenerational education mobility. Consistently, trade shock on low-skilled labor-intensive industries mainly drives the results.

Second, we provide empirical evidence to reject the notion that changes in the opportunity cost of education solely explain the baseline results in this study. The opportunity cost of education is directly related to the wage premium of receiving more education. Using UHS data, we estimate the trajectories of the wage premium of high school education in both high- and low-exposure regions. We find that cities with a below-median level of export tariff shock witnessed a downward trend of wage premiums, while cities with an above-median level of shocks had a more stable wage premium. Additionally, the skill premium in cities with an above-median level of shocks is not lower than that in cities with below-median shocks in 2005-2009. These results contradict the prediction that high-exposure regions should have a lower wage premium after the accession to the WTO if the opportunity cost of education increases more in those regions than in low-exposure regions.

Third, using census, CFPS, and CHIP data, we find that trade shock negatively affects educational outcomes for preschool children and children taking compulsory education. This effect cannot be explained by the opportunity cost of education because these children do not face the trade-off between continuing education and entering the labor market at such a young age.[3] Instead, this result is related to the aforementioned income effect and substitution effect. Using census data, we find that the reduction in export tariff significantly

[3]Forward-looking parents may adjust their investment in children's education if they anticipate an increased opportunity cost of education. This study regards this as the human capital investment channel instead of the opportunity cost channel.

increases the probability of children being separated from their parents, providing direct evidence to support the substitution effect channel. As shown in the CHIP data, school quality for children from low-educated families does not improve. Also, household expenditure on education does not increase significantly, suggesting that the income effect cannot compensate for the substitution effect in our context.[4]

This study contributes to several growing streams of literature. First, it adds to research on trade liberalization's impact on education and human capital investment (Atkin, 2016; Blanchard and Willmann, 2016; Blanchard and Olney, 2017; Khanna et al., 2020; Leight and Pan, 2023; Li, 2018, 2020; Lin and Long, 2020). Our findings align with previous studies showing that trade liberalization can decrease educational attainment (Atkin, 2016; Blanchard and Olney, 2017; Leight and Pan, 2023). However, we extend this literature in important ways. While most previous studies emphasize the opportunity cost mechanism in explaining trade liberalization's impact on human capital investment decisions, we demonstrate that this mechanism alone is insufficient. Our analysis reveals that the wage premium for higher education is not greater in high-exposure regions, contrary to what the opportunity cost hypothesis would predict. Moreover, we find effects on early childhood development, which cannot be explained by opportunity cost. Instead, we propose that parental decisions on human capital investment are crucial, particularly how parents balance new job opportunities with time spent on their children's education.

Second, we contribute to literature on trade liberalization and social equity, specifically intergenerational education mobility. Our findings contrast with studies like Ahsan and Chatterjee (2017) and Mitra, Pham and Ural Marchand (2022), which found positive effects of trade liberalization on mobility in India and Vietnam, respectively. These differences may be attributed to varying contexts and labor market dynamics across countries. Our results

[4]We cannot fully rule out other potential channels in this study due to data limitations. For example, the composition of teachers may be affected by the trade shock if some teachers switch to other occupations. We argue that the substitution effect plays a role in explaining our results.

align more closely with Cai and Xu (2022), who also used Chinese data. Our study differs significantly from Lou and Li (2022) in both data sources and methodology. While they used the 2010 China Family Panel Studies dataset, we employ multiple waves of population census data, offering a larger sample size and broader geographical coverage. Our cohort Difference-in-Differences design allows for a more robust causal inference by exploiting both temporal and spatial variations in trade exposure.

Third, our work connects to literature on children's development and social mobility (Chetty et al., 2014; Chetty, Hendren and Katz, 2016; Chetty and Hendren, 2018; Heckman, 2008; Heckman and Mosso, 2014; Heckman and Landersø, 2021). We emphasize the importance of parental time and effort in children's education, aligning with existing research on the crucial role of family interventions in child development. However, our findings diverge from some previous studies in an important aspect: we find no evidence of an income effect compensating for the negative substitution effect. This contrasts with findings in different contexts, such as Nicoletti, Salvanes and Tominey (2023) in Norway, where increased family income from mothers' work was found to offset reduced time spent with children. Our results suggest that in the context of China's trade liberalization, increased family income did not translate into greater investment in children's education, highlighting the complexity of these relationships across different economic and cultural settings.

Our study thus provides novel insights into the intricate relationships between trade liberalization, parental investment, and intergenerational mobility. By examining both direct and indirect channels through which trade shocks affect educational outcomes, and by leveraging comprehensive data and robust methodological approaches, we contribute to a more nuanced understanding of these interconnected phenomena. This work not only advances academic discourse but also has important implications for policymakers considering the long-term social impacts of trade policies.

The remainder of this paper is organized as follows. section 2.2 introduces the institutional background of this study and proposes the conceptual framework that guides the empirical analysis in this paper. section 2.3 describes the data and measurements used in this study. section 2.4 proposes the empirical analysis design and corresponding results. section 2.5 discusses the mechanisms. Finally, section 2.6 concludes this study.

2.2 Background and Conceptual Framework

2.2.1 China's accession to the WTO

Trade liberalization occurred in many developing countries in the past decades. Among them, China's accession to the WTO in 2001 did much to reshape the Chinese economy. Starting from the early 1990s, the Chinese government took several measures to reduce trade barriers with other countries. For example, the range of tariff-exempted import goods expanded significantly. Throughout the process of entering the WTO, as well as in the first few years after joining, the average import tariff reduced significantly in China (refer to Figure 2.1). As documented in Brandt et al. (2017), both output tariffs and input tariffs dropped substantially, with the median value dropping from above 20 percent to below 10 percent. Large-scale tariff cuts lead to intensified market competitions (Lu and Yu, 2015), worse labor market conditions for workers (Dai, Huang and Zhang, 2020), a surge of imported capital goods (Li, 2020), among other impacts (refer to, e.g., Dai, Huang and Zhang, 2021; Erten and Leight, 2021; Cheng and Potlogea, 2017).

On the other hand, other countries' tariffs imposed on China's export goods declined as well. As shown in Figure 2.2, the average tariff rate of several major economies dropped in the period of 2001 to 2006. Among these changes, the most notable one is the legislation of permanent Normal Trade Relations (NTR) with the US. Before the legislation, tariff rates on China's export goods were subject to Congress's annual renewals. After the legislation, tariff rates are set to the known NTR level. Therefore, the legislation reduced trade policy uncertainty between China and the US by a lot.[5] With the reduction in export tariffs, the

[5]Lot of research uses the variation in trade policy uncertainty as an exogenous shock to

export sector expanded by a lot following accession to the WTO. As shown in Figure 2.3, the ratio of international trade to GDP increased rapidly in the period from 2000 to 2006.

2.2.2 Education System in China

Prior to age six, children in China may take preschool education. However, preschool education is not prevalent in China, especially when we look back at the early 2000s. According to the 2000 population census in China, about 45 million children aged between 3 to 5 years old. Among them, only about 22 million took preschool education in 2000. Therefore, the academic preparation of children under six years old depends highly on family education. According to several papers, caregiver-children interaction is quite low in rural China (refer to, e.g., Luo et al., 2019; Wei et al., 2015; Yue et al., 2019). Parents seldom tell stories or play with their children. The heterogeneity in early childhood development may be crucial in explaining long-term academic performance heterogeneity.

Children aged six years or above enjoy a nine-year compulsory education in China, including six years of primary education and three years of lower-secondary education. As pointed out by Machin, McNally and Ruiz-Valenzuela (2020), access to post-compulsory education is important for students' perspective in the labor market. After the compulsory educational period, students can enter high schools or technical schools. In 2001, the proportion of middle school graduates that took post-compulsory education was only 58.3%, meaning that about 40% of middle school graduates entered the labor market directly.[6] Given this fact, in this study, we will use whether a student takes post-compulsory education as one outcome variable.

In general, students and parents in China prefer high schools to technical schools (Hansen

study the impact of trade liberalization. Refer to, for example, Khanna et al. (2020); Erten and Leight (2021); Facchini et al. (2019); Pierce and Schott (2016).

[6]In 2019, the proportion of middle school graduates that took post-compulsory education had reached 91.2%. However, the ratio of high school entrants to middle school graduates was 57.1%, meaning that more than one-third of middle school graduates take vocational education.

and Woronov, 2013; Wu and You, 2020). However, entering high school is subject to fierce competition in the High School Entrance Exam (HSEE). After three years of high school education, students can take the College Entrance Exam (CEE) to pursue tertiary education. Admission to colleges and universities is highly dependent on performance in the CEE. Therefore, students spend most of their time preparing for the exam in high school. Taken together, secondary education in China is largely exam-oriented. Based on this feature, students and parents care much about their performance in examinations. As pointed out later in section 2.4, parents' subjective evaluation of their children's exam performance is highly correlated with the related cognitive skills of children, meaning that parents can tell the academic capacity of their children. Therefore, we can use parents' subjective evaluation to measure children's educational performance. Under the assumption that the relationship between parents' subjective evaluation and children's actual performance remains constant before and after the trade shock, we can use parents' subjective evaluation to investigate how the trade shock affects children's educational performance.

2.3 Data and Measures

2.3.1 Individual-level Data

The primary dataset employed in this study is 2000, 2005, 2010, and 2015 population census data, each covering 0.09%, 0.20%, 0.30%, and 0.15% of the total population, respectively. The Chinese census is the most representative data for employment analysis because it draws a systematic sampling from the entire Chinese population. Individual-level Chinese census also provides comprehensive information on individual characteristics for each observation, including age, gender, education, industry, location, employment status, and migration and registration status information.

One advantage of the census data is that it records the relationship between the interviewees and the household head so that we can match the child with their parents and form child-parent pairs. Four types of child-parent pairs are certain in the data: household head and his/her parents; spouse of household head and parents-in-law of household head; household head and his/her children; and siblings of household head and the parents of the household head. For these individuals, we can identify their co-residency with their parents. Also, if they live with their parents, we know the information about their parents. We identify the co-residency of 86.70%, 87.97%, 85.97%, and 88.15% of individuals in each wave of the census data and drop the rest that cannot be identified.[7]

Our empirical analysis focuses on people aged between 16 to 35 years old at each round of the census. Cohorts born in or after 1985 were not older than 16 in 2001 and were exposed to trade shock when making education decisions. For education mobility analysis, we match parent-child information for each census, then combined the data from the 2000-2015 censuses to form pooled, cross-sectional data.

The summary statistics are provided in Table 2.1. 55.9% of individuals in our combined sample live with at least one of their parents. The average level of education is longer for children than for both parents. The mother's education year is lower than the father's. We use the data for those who have finished education throughout the analysis, assuming they will not return to school. Panel A of Figure 2.4 shows that the largest increase in upward mobility occurred between 2000 and 2010, particularly in inland areas. Table 2.2 displays the transition matrix of parental-child education of all workers aged 16 to 35. It reveals a significant upward mobility in education, especially for people from low-educated families, which could be ascribed to the expanding compulsory education and local education enhancement in recent decades. We also calculate the proportion of workers who have achieved a higher education than their parents, stratified by parents' education. More than half of the workers attain higher degrees than their parents.

[7]Whether one's co-residency with parents or children can be determined depends solely on which of his/her household member was included as the household head in the census. Therefore, as long as the census is random and nationally representative, the identifiability of co-residency is exogenous and sample selection should not be an issue.

We incorporate several data sets to conduct the mechanism analysis. One data set is the Urban Household Survey (UHS) from 2002 – 2009, collected by the National Bureau of Statistics of China (NBSC). The UHS is the most comprehensive household survey in urban areas in China, and it provides a detailed record of urban residents' demographic, employment, and income information. A restriction of the dataset is that it only contains urban households in 185 cities (out of about 300). Yet, the survey design ensures the national representativeness of the data. We also utilize the Chinese Household Income Project (CHIP) and the China Family Panel Study (CFPS) data. CHIP was implemented in 1989, 1996, 2003, 2008, and 2013. The CHIP 2007 and 2008 used in this study covered 8000 rural and 5000 urban households residing in 67 cities in ten provinces in China's eastern, central, and western regions. The CHIP data provides information about children's performance during the compulsory education period. CFPS is a nationally representative, biannual longitudinal survey of Chinese communities, families, and individuals launched in 2010, covering almost 15,000 families and 30,000 individuals within these families. It is also a good resource for assessing the early educational performance of children.

2.3.2 Measurement of Trade Shocks

In the analysis, we analyze the impacts of trade liberalization by constructing three Bartik-type shocks, all of which are weighed by the initial share of industry j city c in 2000.[8] Of them, we particularly focus on the effects of average export tariff reduction among industrial sectors. The weighted average 6-digit HS tariff imposed by other countries on goods imported from China each year comes from the WITS TRAINS database, and we focus on the period 2000-2006, which experiences the most dramatic decline in average export tariff.[9]

[8]Bartik (1991) first develops this class of instruments to estimate the impact of county-level employment changes on wages. In recent years, this type of instrument has been widely adopted (Dai, Huang and Zhang, 2021; David, Dorn and Hanson, 2013; Li, 2018, among many others.)

[9]The database calculates aggregate HS-level export tariffs by weighting all importers' trade value in a year. We first map the HS 6-digit code to the Chinese industry classification

The measurement is constructed as follows:

$$ExpShock_c = \sum_j empshare_{2000,cj} \times [\ln(1+\tau_{j,2000}) - \ln(1+\tau_{j,2006})]$$

where $empshare_{2000,cj} = \frac{E_{2000,cj}}{E_{2000,c}}$ is the initial share of industry j's employment in city c in 2000. Besides, we also control for (1) the reduction in trade uncertainty measured by

$$NTRGap_c = \sum_j empshare_{2000,cj} \times NTRGap_j$$

where $NTRGap_j = NonNTRrate_j - NTRrate_j$ measures the tariff faced in US markets,(2) change in average import tariff during the same period which is constructed similarly to the export tariff.[10], and (3) shift-share import and export tariff rate in city n for i at age 16.

In the last section, we show that the average industry export tariff decreased in the years after 2000, accompanying rapid growth in export. Panel B of Figure 2.4 shows that the exposure of export tariff reduction concentrates on coastal and northeastern areas, which is largely different from the spatial distribution of the increase in the proportion of families with upward education mobility as shown in panel A. Figure B1 in the appendix shows that the variation of export tariff reduction is large within each 2-digit sector.

(CIC) version 1994 and then aggregate the average HS export tariff with their export share to get the 3-digit level CIC export tariff.

[10]Here, we follow Pierce and Schott (2016) and measure the uncertainty associated with China's temporary normal trade relations (NTR) status before 2001 as the NTR gap, which is defined as the difference between the tariff rates imposed on trade partners with NTR and the tariff rates on other trade partners.

2.4 Empirical Analysis

2.4.1 Baseline Specification

The main interest of our study is to identify how trade liberalization affects educational attainment in China. The baseline model applies a standard cohort DID regression. Low-educated families are defined as households where neither parent has obtained an upper secondary education and high-educated families include at least one parent who has completed upper secondary education or holds a higher degree.

$$Y_{ibct} = \beta_1 ExpShock_c \times Treat_i + \alpha OTS_c \times Treat_i + \Gamma X_{ibct} + \gamma_{ct} + \gamma_{bt} + \epsilon_{ibct} \tag{2.1}$$

Where i denotes each individual, b denotes one's birth year (cohort), c denotes the survey city and t is the census year. Y_{ibct} stands for two key outcome variables considered in this study: (1) whether i has a higher education level than the highest education level of parents,[11] (2) whether i has taken upper secondary education. The key independent variable is the interaction term of individual-level treatment dummy based on the birth year, $Treat_i$, and the city-level reduction in export tariff is $ExpShock_c$. OTS_c include a set of trade shock measures, such as the reduction in trade uncertainty and import tariff. γ_{ct} capture the city-census year trend, and cohort-census year fixed effects are absorbed in γ_{bt}. β_1 is the coefficient of interest, which captures the effect of export tariff reduction on education for the treated group.

In China, the probability of leaving school rises dramatically after age 16, when one finishes his/her compulsory education. Therefore, youth born before 1984 are defined as the control group, while those born in 1984 or afterward are defined as the treated group where $Treat_i = 1$. The reason for choosing this birth cohort threshold is that by 2000 (just

[11] We also try alternative measures, e.g., the average education year of parents, and the results are robust.

before China's accession to the WTO), people who were born after 1984 were 16 years old at the most, so they were at or below the age of deciding whether to pursue upper secondary education or not. Additionally, we also construct the treatment intensity variable to capture the different degree of exposure to reduction in trade uncertainty. Specifically, we use the time an individual experienced after China entering WTO before he turns 16[12]:

$$Treat\_Intensity_i = \begin{cases} 0, & b \leq 1984 \\ 1 - \dfrac{2000 - b}{16}, & b > 1984 \& b < 2001 \end{cases} \tag{2.2}$$

Our identification strategy critically hinges on the several assumptions, including the parallel-trend assumption(PTA), stable Unit Treatment Value assumption, and no anticipation. PTA implies that for the treated cohorts, each city's cohort trend in education should not be correlated with the trade shock in the absence of China's accession to the WTO. We later provide evidence to support the parallel-trend assumption and implement a series of robustness checks.

We also need to deal with the co-residence selection bias when using census data. The population census usually does not record the information of the members who are not living in the house, so we cannot get the education level of those who do not live with their parents. If living with parents is not randomly decided, then there is a sample selection bias. We deal with this problem using the propensity score weighting method suggested by Francesconi and Nicoletti (2006), which is adopted by Ahsan and Chatterjee (2017) to deal with similar issues. In the first step, we run a logit regression on the whole sample: $P(coliving = 1) = f(X'\beta)$ where X consists of a set of individual-level characteristics: age and its squared term, as well as indicators for school, work, hukou status, marital status, and ethnicity. We also control for province fixed effects and year fixed effects. We use the

[12] We choose the cutoff age at 16 instead of 15 as in Erten and Leight (2021) because in some regions, children's earliest age of entering primary school is seven instead of six according to the compulsory education law, so they are already 16 when finishing the compulsory education.

inverse of the estimated probability to estimate Equation 2.1 in the second step.

After presenting the standard cohort DID regression, we use an alternative by-cohort regression following Duflo (2001) to separately estimate the effects of trade shock on each cohort. We classify a cohort as those born within subsequent two years and use the following specification (using the who born in 1983 as the omitted group)[13]:

$$\begin{aligned} Y_{ibct} = & \sum_{b=1970, b\neq 1983}^{1996} \beta_b (ExpShock_c \times I_b) + \\ & \sum_{b=1970, b\neq 1983}^{1996} \alpha_b (OTS_c \times I_b) + \gamma_{ct} + \gamma_{bt} + \Gamma X_{ibct} + \epsilon_{ibct} \end{aligned} \tag{2.3}$$

I_b equals one if individual i belongs to cohort b and zero otherwise. Specifically, I_{1974} stands for all cohorts on or before 1974, and I_{1996} stands for all cohorts on or after 1996. The primary coefficient of interest is β_b, which reflects the impacts of trade shock for different cohorts.

2.4.2 Discussions on Casual Inference

Our empirical specification utilizes a difference-in-differences design with a continuous treatment. Callaway, Goodman-Bacon and Sant'Anna (2024) discussed different assumptions and the importance of interpreting differences in these parameters across different values of the treatment. The identification strategy critically hinges on the parallel-trend assumption: for the treated cohorts, each city's cohort trend in education should not be correlated with the trade shock in the absence of China's accession to the WTO. We later provide evidence to support the parallel-trend assumption and implement a series of robustness checks.

[13] Considering the sample size, people born before 1973 are categorized to the first group and born after 1993 are categorized as the last one.

2.4.3 Baseline Results

We present our baseline estimates in Table 2.3. Panel A displays the results concerning high school degree attainment, while Panel B focuses on upward educational mobility. Columns (1), (3), and (5) illustrate the outcomes for young workers from low-skilled families, whereas Columns (2), (4), and (6) depict the results for those from high-skilled families. For young workers from low-skilled families, the coefficient β_1 in Panel A of Column (7), indicates that a one standard deviation increase in exposure to export tariff reduction correlates with a 0.74 percentage point decrease in the probability of high school attainment. Similarly, Panel B shows a 0.67 percentage point decline in upward educational mobility. These results are insignificantly positive for those from skilled families, as demonstrated in the even-numbered columns.

The heterogeneous impacts on young workers from different family backgrounds may stem from the fact that parents with lower education levels tend to invest less time and effort in their children's education compared to highly educated parents. They are also more sensitive to labor market shocks, making their educational investment in their children more responsive to exogenous factors. The coefficient of $Exptar_{16}$ captures the effect of export tariff exposure at age 16, highlighting the persistent impact of export shocks during 2000-2006 on those about to enter the labor market. Although the coefficient is positive, implying that lower export tariffs reduce educational attainment, it remains insignificant and does not alter the coefficient β_1.

Figure 2.6 illustrates the coefficients of export tariff reduction for each cohort born between 1970 and 1996 on educational outcomes, based on the estimation method described in Equation 2.3. Panels A and B display trends for workers aged 19-35 in each census. The coefficients are not statistically significant for cohorts born before 1984, suggesting no heterogeneous cohort trends in education relative to city exposure to export tariff changes before the treatment period. For cohorts born after 1984, most coefficients are significantly negative. Generally, the negative impact intensifies for cohorts born between the late 1980s and early 1990s, but diminishes for those born after 1995. This pattern indicates a long-term effect of trade liberalization in the early 2000s rather than a temporary shock[14]. The coefficients of NTRgap on both outcomes show similar trends, whereas the coefficients of import tariff reduction exhibit increasing positive impacts on high school attainment for the initial cohorts, but they do not meet the parallel trend assumption for upward educational mobility, as shown in Panels A and C of Figure B3.

2.4.4 Robustness Check

In this section, we conduct a battery of robustness checks further to validate the identification of our baseline empirical analysis. (1) We replace the dummy treatment with the treatment intensity to reflect the extent of exposure; (2) We exclude western regions in our regression to address the concern that the high education upward mobility in some parts of western areas such as Xinjiang and Xizang could drive the negative relationship between trade shock and education mobility; (3) We restrict the sample to those with local hukou and perform additional bootstrap clustering at the provincial level to allow for intra-provincial correlation, considering that trade-induced massive internal migration flow may affect local skill composition (Leight and Pan, 2021); (4) we address the concern that some individuals may self-select negatively into the labor market at a young age by expanding our sample to include all youth above 16, including those still in school[15]; (5) We perform a falsification test that uses a fake timing of the trade shock to define the "treatment group" and the "control group"[16]. (6) We rule out that omitted variable bias drives our results with the method proposed by Oster (2019). (7) We validate that city-level export tariff reduction constructed in a shift-share way captures the exogenous variation of export tariff. Finally, we also conduct sensitivity analysis on the pre-parallel trend following Roth (2022)'s method.

[14]We also explore an alternative specification that combines two birth years into one cohort, with results presented in Appendix **??**.

[15]Census data record the current degree a person is trying to complete if he is at school, so the education level of those who are studying in high school at the survey time is defined as high school degree.

[16]We take the cohorts born between 1978 and 1984 as the falsely treated cohorts.

Results of robustness checks (1) – (5) are summarized in Table 2.4. Panel A reports the results of getting a high school or above education. Panel B reports the results of getting more education than one's parents. Column(1) shows that one year more exposure to trade shock is associated with around 0.13% more decline in marginal effect of trade shock on high school attainment and upward mobility. Column (2) shows that β_1 even becomes more negative when excluding the western areas, and column(3)(4) show the result is stable among different samples. Column (5) demonstrates that using cohorts after 1980 yields similar results to the baseline specification, ruling out that compulsory education law drives the results. In column(6), we show the results of unweighted regression with bootstrap standard errors clustered at provincial levels. We find the different cluster method does not affect the value of β_1. The result of robustness check (6) is shown in Table 2.A.1, which is consistent with our baseline results in the previous section.

Omitted Variable Problem

China changed in many ways during the trade liberalization period. Some changes may have heterogeneous effects across cohorts and geographies in a way that is correlated with the trade shocks considered in our many analyses. For example, the large-scale increase in enrollment slots to universities starting in 1999 may affect the education decisions of different generations and different regions.

Although we control for an abundant set of controls in the basic regression, there is still the concern that the city-by-cohort omitted variables may negatively correlate with trade shock and bias our estimates. We use the method proposed by Oster (2019) to evaluate how large the bias due to unobservables should be, in comparison to that due to observables, in order to explain away the estimated effect. The ratio between the bias caused by unobservables and controls is δ. We follow the recommendations and calibrate the maximum R2 to 1.3 times the estimated R2 from the regression with a full set of controls, and present the ratio that matches a zeros treatment effect. Table 2.A.2 shows the results. Both Oster ratios are larger than 1, implying that the selection on unobservables must be larger than the selection on observed variables to fully explain the effect, which is unlikely given that we have already controlled for a large set of covariates.

Validity of Bartik Approach

Recent literature on the exogeneity of the shift-share measure highlights two alternative frameworks in which the exclusion restriction may hold. One is based on the quasi-randomness of aggregate shocks (Borusyak, Hull and Jaravel, 2022) and the other is based on the quasi-randomness of local shares (Goldsmith-Pinkham, Sorkin and Swift, 2020). In the context of trade liberalization, we regard the tariff reductions of different countries and products to be exogenous. Therefore, the framework in Borusyak, Hull and Jaravel (2022) suits the setting of this paper better. Their framework has two critical assumptions to satisfy the large-N asymptotic approximation for characterizing the finite sample behavior of the shift-share estimator: (1) shocks are quasi-randomly assigned; (2) there are many uncorrelated shocks. It is important to ensure that we have enough variations in tariff shocks across industries, and we adopt the strategy proposed by Borusyak, Hull and Jaravel (2022) to support these assumptions.

We support the first assumption by conducting balance tests on industries and regions. We separately regress the initial industry employment share, skill intensity, predicted export value, and import value on export shocks. Results in Table 2.A.3 show that almost all coefficients are statistically insignificant or extremely small in magnitude. The results indicate that the size of export tariff reduction is uncorrelated with industrial characteristics. we perform balance tests on regions by using city-level log trade volume per capita, the proportion of low-skilled workers, the share of females, and the share of young workers as explanatory variables to reflect the initial composition of regional workers. We then regress them on city-level export shocks.[17] Table 2.A.4 shows that there are no statistically significant relationships between these variables and the shift-share shock. These results indicate that the orthogonality of shocks is likely to be held.

[17]The detailed implementation follows Borusyak, Hull and Jaravel (2022).

For the second assumption, Table 2.A.5 reports summary statistics for the export tariff shocks computed with importance weights of industry employment share in the year 2000 and characterizes these weights. Column (1) includes all industries and column (2) excludes agriculture and other industries with missing trade shocks. Agriculture accounts for about 60% of the total employment in China in 2000, which is the largest and most dominating industry. Therefore, it results in a high concentration degree and a small effective sample size at an aggregate 2-digit industry level.[18] Including agriculture would likely violate assumption (2). Excluding agriculture and other missing industries makes the largest share fall to 9%, the effective sample size goes up to 56.3, and the standard deviation increases as well, leading to a more dispersed distribution of shocks. A sizable degree of variation at the industry level (as shown in Figure B1) also supports the assumption (2).

Sensitivity of Pre-Parallel Trend Assumption

As highlighted by Callaway, Goodman-Bacon and Sant'Anna (2024), varying assumptions about parallel trends can yield divergent interpretations of our estimates. Despite controlling for city-level interaction terms and cohort trends, the assumption's potential violation due to disparate confounding factors across cohorts remains plausible. Section 2.4.3's pre-trend tests offer a preliminary assessment of this assumption, but they are subject to limitations. First, these tests may lack sufficient power to detect violations. Second, analyzing only cases with non-significant pre-trends could introduce selection bias within our sample.

To address these concerns, we employ the robust inference approach proposed by Rambachan and Roth (2023). This method imposes smoothness restrictions, assuming that the slope of trend differences does not exceed a specified threshold M between periods. We calculate the breakdown value, indicating the maximum change in trend slope that the estimate of average treatment effect (ATT) can withstand before the parallel trend assumption is invalidated. Figure 2.7 displays these results across different treated cohorts.

Our findings reveal that cohorts born after 1988 exhibit consistently larger negative

[18] Column (1) shows the number is only 2.8.

impacts. Notably, the breakdown point for both early and late cohorts is 0.0003, suggesting that the parallel trend assumption could be violated if the slope of pre-trends changes by more than 43% of the estimated ATT (-0.0007). In contrast, the middle cohort (1988-1992) demonstrates the strongest and most robust negative effects, requiring a significantly larger change in slope to invalidate the assumption. Conversely, the late cohort (1992-1996) mirrors the early cohort's breakpoint, indicating an inverse-U pattern in the impacts of trade liberalization on education.

2.4.5 Heterogeneity Analysis

In this section, we examine the heterogeneous effects of export tariff reduction on education from three perspectives: differences in exposure based on skill intensity, the influence of parents' occupational sectors, and varying effects across family sizes.

According to the Stolper-Samuelson theorem, countries abundant in unskilled labor are likely to export goods requiring more unskilled labor, thereby expanding job opportunities in this sector and potentially increasing the opportunity cost of pursuing education. Table 2.5 illustrates that reductions in export tariffs decrease educational attainment among individuals from unskilled labor families. Specifically, a one standard deviation decrease leads to a 1.5% decline in the likelihood of attaining a high school degree or higher, and a 1.7% decrease in upward mobility.

Table 2.6 further explores the heterogeneous effects across different family sizes and parental industries. Columns (1) and (2) reveal that these negative impacts are more pronounced for young workers whose parents work in industrial sectors, with effects nearly tripling compared to those from agricultural backgrounds. This aligns with the observation that the income effect from trade is stronger among unskilled agricultural families. Columns (3) and (4) indicate that the effects are more significant for only children, suggesting that being an only child motivates youth to enter the labor market earlier to support their families financially, compared to those with siblings[19].

2.5 Mechanism

2.5.1 Opportunity Cost of Education

This part tries to estimate whether a change in the opportunity cost of education explains the effect of export tariff reduction on youth education.

We utilize the Urban Household Survey (UHS) data covering the period from 2002 to 2009, which contains information on individual wage income and education status. We use this data to measure the wage premium of urban workers with at least a high school education. Following the argument in section 2.3, if export tariff reduction mainly increases demand for low-skilled workers, which drives up their wages, we should find that skill premiums in the more affected areas should be lower than that in less affected areas. To test this conjecture, we conduct the regression as below:

$$\log(wage_{it}^S) = \beta_0^S + \sum_{t=2002}^{2009} \beta_{1t}^S HS_{it}^S \times Year_t^S + \beta_2^S X_{it}^S + \lambda_c^S + \lambda_t^S + \varepsilon_{it}^S, \quad S = A, B \tag{2.4}$$

where $\log(wage_{it})$ is the logarithm of wage (measured in 2002 price level) of individual i in year t. HS_{it} indicates if individual i has at least a high school education by year t. $Year_t$ is a set of dummies indicating each year. X_{it} is a set of individual controls, λ_c and λ_t captures city and year fixed effects, respectively. ε_{it} is the error term. β_{1t} is a set of coefficients of interest, which capture the wage premium of high-school-or-above education in each year in the sample period. Specifically, we estimate this model separately for two sub-samples, $S = A, B$, where $S = A$ means individuals in cities faced an above-median level of export tariff reduction, and $S = B$ means individuals in cities faced a below-median level of export tariff reduction. To be consistent with our baseline specification, we restrict the sample to

[19]Data limitations prevent a direct comparison of the effects on older versus younger siblings.

individuals aged between 16 and 35 years. Such specification captures more precisely the skill premium of new entrants to the labor market.

Results are shown in Figure 2.5. In Panel A, the skill premium in cities with above-median export tariff shock were quite stable from 2002 to 2008 and significantly decreased in 2009. On the contrary, as shown in Panel B, the skill premium dropped significantly in cities with below-median shock as early as 2005 and stayed significantly lower than the 2002 level from then on. Moreover, the skill premium in cities with above-median shock is not lower than that in cities with below-median shock in 2002–2009 (if anything, the former is higher). Therefore, reduced skill premium, which means the increased opportunity cost of education, should not be the main driving force of reduced education of those who enter the labor market after the trade shock (refer to Figure 2.6). To further quantify the impact of export tariff shock on skill premium across time, Table 2.A.6 includes a three-way interaction term of HS, $Year$, and $ExpShock$ in Equation 2.4. The results indicate that the skill premium is never significantly lower in regions experiencing an above-median reduction in export tariff than in below-median-exposure regions.

2.5.2 Human Capital Investment for the Next Generation

This part proceeds as follows: we first provide evidence that the educational performance of children under 16 years old is also negatively affected by a reduction in export tariff, which is unlikely to be explained by the opportunity cost hypothesis, but rather is more likely to be explained to human capital investment on children.[20] With the results at hand, we further provide direct evidence that a reduction in export tariff leads to a higher probability of children being separated from their parents.

We focus on two groups of under-16 children. The first group includes preschool children,

[20]Here we define the opportunity cost channel works only through the direct trade-off between taking more education or entering the labor market. We cannot rule out the case that forward-looking parents may change their investment in children's human capital based on their perception of the opportunity cost of education. However, we take that as the mechanism explored in this section as well.

while the second group includes children taking compulsory education.

For preschool children, we utilize the information from census data about whether one is literate. Specifically, we focus on children aged six years, i.e., those who just entered or are about to enter a primary school. The literacy of this group of children indicates the quality of early childhood development before formal school education. As shown in Figure B2, for the pooled sample of census data, the city-level average literacy rate is about 85% for 6-year-old children and reaches about 100% from seven years old onward. Therefore, focusing on 6-year-old children provides sufficient variation for analysis. The empirical model is specified as follows:

$$Literate_{it} = \beta_0 + \beta_1 Treat_{it} \times ExpShock_c + \beta_2 X_i + \gamma_c + \gamma_t + \varepsilon_{it} \tag{2.5}$$

where $Literate_{it}$ equals one when a child i who ages 6 years in year t is literate at that time and zero otherwise. $Treat_{it}$ equals one for 6-year-old children in the 2005–2015 census data as their early childhood is assumed to be affected by the trade shock. $Treat_{it}$ equals zero for 6-year-old children in the 2000 census data, as their preschool development is not affected by the trade shock. $ExpShock_c$ is the measure of trade shock, representing export tariff reduction as defined in section 2.3. X_i includes individual-level covariates such as gender, ethnicity (Han people or not), and rural Hukou status. γ_c and γ_t are city and year fixed effects, respectively. ε_{it} is the error term.

We estimate Equation 2.5 on pooled 2000 – 2015 census data of 6-year-old children. Results are shown in Table 2.7. Treated children are less likely to be literate at six when faced with larger export tariff reductions. It indicates that early childhood development is negatively affected by export expansion. However, such effects occur only in children from low-educated families (Columns (1) – (3)) but not in children from highly-educated families (Columns (4) – (6)), consistent with the results above. It is worth noting that preschool education is not compulsory in China. Therefore, the quality of early childhood development depends on home education (substitution effect) and the quality of preschool education (income effect). Due to data limitations, we cannot separately identify the role of these two effects in this analysis. Later we show that the income effect is not significant for children from low-educated families, and we provide direct evidence for the substitution effect.

To analyze the impact of the trade shock on compulsory education, we use the China Household Income Project (CHIP) data, which is a longitudinal dataset that tracks households in rural and urban areas of China. The dataset includes five waves of surveys conducted in 1988, 1996, 2007, 2008, and 2013. To ensure a pre- and post-trade shock sample of children aged between 6 and 16 years, we use data from 2007 and 2008. The dataset links children with their parents and other family members and provides information on their educational performance. Our analysis includes measures related to children's education, such as parents' subjective evaluation of their child's performance, subjective evaluation of school quality, time spent on study, and expenses on education. We identify a sample of 6,780 children from 5,689 households for this study. In Table 2.A.7, we use CFPS data to demonstrate that parents' subjective evaluation is significantly related to children's cognitive skills, indicating that subjective evaluation can serve as an informative predictor of actual educational performance.

Results as shown in Table 2.8. The reduction of export tariffs significantly decreases educational performance for treated children from low-educated families. The impacts on study time and education expenses are not significant. The impacts on education performance for children from highly educated families are not significant, which is consistent with the results presented earlier. However, the school quality increases for treated children from high-educated families. Notably, the (non-significant) negative impacts on school quality and the non-significant impact on educational expenses for children from low-educated families are inconsistent with the income effect hypothesis. To provide additional evidence, we use the UHS data in Table 2.A.8 to show that households in cities with a larger reduction in export tariff do not spend more on education than other households, even though their total income and expenditure increase with a reduction in export tariff. Taken together, we conclude that the income effect cannot compensate for the negative educational outcomes of children from low-educated families in our context.

Finally, we provide direct evidence that a reduction in export tariffs leads to increased separations between parents and children. We define parents as absent if either of them is not living with their under-18 children at the time of the census. There are many potential reasons for a separation between parents and children. In this study, we hypothesize that increased job opportunities created by the trade shock in coastal regions attract workers from inland regions to migrate to coastal regions, leading to parent-child separation. To test this hypothesis, we utilize multiple waves of census data and follow the specification in Equation 2.5 to estimate how a reduction in export tariff affects the probability of being separated from parents. The regression model is specified below:

$$Absence_{it} = \beta_0 + \beta_1 Treat_{it} \times ExpShock_c + \beta_2 X_i + \gamma_c + \gamma_t + \varepsilon_{it} \tag{2.6}$$

Results are shown in Table 2.9. As shown in Columns (1)-(2), a reduction in export tariff significantly increases the probability of treated children being separated from at least one of their parents. Comparing the results in Columns (3) and (4) as well as Columns (5) and (6), we can see that the effect is mainly driven by low-educated families, which is consistent with the results above. A higher probability of being separated from parents provides direct evidence that a reduction in export tariff negatively affects the time and effort parents spend on their children.

2.6 Conclusion

This study examines the impact of a reduction in average export tariff other countries imposed on goods from China on intergenerational education mobility, during trade liberalization. Using separate cohort difference-in-differences (DID) regressions on workers with different levels of parental education, this study presents new evidence on the parental-investment mechanism.

I find that compared to older workers who were not exposed to trade liberalization, younger generations have a lower probability of completing high school or attaining a higher level of education than their parents when they are in regions that witnessed larger export tariff shocks. However, this trend only applies to children from low-educated families, indicating a decline in intergenerational education mobility. One standard deviation increase in exposure to export tariff shock leads to an additional 0.74% decrease in the probability of attaining a high school diploma for treated cohorts and an extra 0.67% decrease in the probability of educational upward mobility. Our micro-level findings are consistent with recent literature on the impact of trade liberalization on education in developing countries.

In addition to the rising opportunity costs described in most papers, our mechanism analysis reveals a novel long-term channel through which parents spend less time and effort with their children, hindering their human capital accumulation at an early age. Overall, our results suggest that the negative substitution effects outweigh the positive income effects brought about by trade liberalization. Future research could be done to evaluate the welfare effects from a general equilibrium perspective.

Table 2.1: Summary Statistics of Individual Characteristics

	Mean	Median	SD	Min	Max	N
Panel A: Self						
Education	10.27	9	3.11	0	19	2515370
Male	0.54	1	0.50	0	1	2515370
Age	25.87	26	5.84	16	35	2515370
Han People	0.90	1	0.30	0	1	2515370
Num of Children in the family	0.32	0	0.66	0	10	2515370
Working	0.73	1	0.45	0	1	2515370
Agri Hukou	0.70	1	0.46	0	1	2514263
Without Local Hukou	0.10	0	0.30	0	1	2515370
Panel B: Parents						
Father's education	8.39	9	2.93	0	19	1214449
Mother's education	7.13	6	3.39	0	19	1248177
Father's age	51.04	50	7.36	37	72	1214449
Mother's age	49.52	48	7.14	37	72	1248177
Father is Han people	0.91	1	0.29	0	1	1214449
Mother is Han people	0.90	1	0.30	0	1	1248177
Father is working	0.87	1	0.39	0	2	1204446
Mother is working	0.70	1	0.50	0	2	1237777
Father holds agri hukou	0.76	1	0.43	0	1	1214347
Mother holds agri hukou	0.76	1	0.43	0	1	1248079
Father without local hukou	0.02	0	0.15	0	1	1214449
Mother without local hukou	0.02	0	0.15	0	1	1248177

Notes: We focus on the sample from pooled census data of 2000 – 2015 in which children live with at least one of the parents.

Table 2.2: Transition Matrix of Education

Self/Parents' Max education	Primary School	Middle School	High School	College and above	Total
Primary School	66748	23329	4014	210	94301
Middle School	254573	327487	54306	3529	639895
High School	69491	186421	79990	21797	357699
College and above	26540	92122	67267	38722	224651
Total	417352	629359	205577	64258	1316546
Upward Proportion(%)	84.01%	44.25%	32.72%	—-	52.90%

Table 2.3: Effects of Trade Liberalization on Education for different families

Outcome	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High School	Baseline	Baseline	OTS	OTS	Full	Full
Treat×ExpShock	-0.0076***	0.0016	-0.0075***	0.0024	-0.0074***	0.000
	(0.0023)	(0.0048)	(0.0024)	(0.0046)	(0.0023)	(0.0042)
Treat×NTRgap			0.057	0.122*	-0.376**	-0.095
			(0.148)	(0.068)	(0.191)	(0.145)
Treat×ImpShock			0.0435***	0.105***	0.04***	0.1***
			(0.015)	(0.033)	(0.014)	(0.035)
$Exptar_{16}$					0.0403	-0.04
					(0.027)	(0.064)
$Imptar_{16}$					-0.017**	-0.02
					(0.008)	(0.022)
R-squared	0.148	0.175	0.148	0.175	0.151	0.181
Observations	844,580	163,592	844,580	163,592	656,501	138,283
Panel B: Up_eduyear						
Treat×ExpShock	-0.0066**	0.004	-0.006*	0.007	-0.007**	0.00720*
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)
Treat×NTRgap			-0.05	-0.257**	-0.378**	0.312*
			(0.153)	(0.128)	(0.172)	(0.169)
Treat×ImpShock			0.072***	0.068*	0.062***	0.09***
			(0.018)	(0.038)	(0.019)	(0.034)
$Exptar_{16}$					0.033	0.038
					(0.036)	(0.061)
$Imptar_{16}$					0.0072	-0.019
					(0.011)	(0.019)
R-squared	0.261	0.166	0.261	0.166	0.266	0.169
Observations	844,580	163,592	844,580	163,592	656,501	138,283
Sample	Low-Educated	High-Educated	Low-Educated	High-Educated	Low-Educated	High-Educated
Other Trade Shock	No	No	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CityXYear FE	Yes	Yes	Yes	Yes	Yes	Yes
YearXCohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Policies	No	No	No	No	Yes	Yes

Note: Regressions weighted by propensity of coliving. Robust standard errors in parentheses and clustered at city of Hukou, +p<0.1, * p<0.05, ** p<0.01, *** p<0.001. *ExpShock* is the standardized export shock at Hukou place. *Treat* denotes whether individual borns after 1984, $Exptar_{16}$ and $Imptar_{16}$ is the weighted export tariff and import tariff at hukou place for individual i when he/she was 16, as the tariff data covers 1992-2011, this sample only includes those born between 1976-1995. The other policy controls include: the eligibility of exposed to compulsory education law following , the degree of one-child policy stringency constructed using fine rates(**?**), the college students share change between 2000-2005, the non-missed share when matching tariff data to census Borusyak, Hull and Jaravel (2022), the hukou reform index at destination constructed by Fan (2019).

Table 2.4: Robustness Check

Outcome	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High School	Treat_int	Exclude West	Locals Only	All sample 16-35	Falsification	Bootstrap
Treat×ExpShock	-0.02***	-0.009**	-0.007***	-0.007**	0.001	-0.007**
	(0.007)	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
Treat×NTRgap	-1.303***	-0.431*	-0.364*	-0.296	0.154	-0.33
	(0.497)	(0.220)	(0.192)	(0.189)	(0.162)	(0.27)
Treat×ImpShock	0.11**	0.054**	0.041***	0.017	-0.02+	0.044+
	(0.044)	(0.024)	(0.014)	(0.017)	(0.01)	(0.024)
$Exptar_{16}$	0.026	0.02	0.04	0.023		0.06**
	(0.027)	(0.036)	(0.027)	(0.031)		(0.03)
$Imptar_{16}$	-0.014*	-0.018*	-0.017*	-0.025**		-0.02**
	(0.008)	(0.01)	(0.008)	(0.011)		(0.01)
Observations	656,501	548,752	640,319	938,052	446,838	663,800
R-squared	0.151	0.147	0.152	0.155	0.14	0.15
Panel B: Up_eduyear						
Treat×ExpShock	-0.016*	-0.009**	-0.007**	-0.007**	0.001	-0.006*
	(0.01)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Treat×NTRgap	-1.435***	-0.295	-0.362**	-0.291*	-0.12	-0.38
	(0.425)	(0.181)	(0.173)	(0.159)	(0.14)	(0.24)
Treat×ImpShock	0.191***	0.054**	0.063***	0.065***	0.028*	0.07***
	(0.048)	(0.021)	(0.019)	(0.015)	(0.015)	(0.027)
$Imptar_{16}$	0.011	-0.003	0.008	0.012		0.000
	(0.011)	(0.01)	(0.011)	(0.011)		(0.000)
$Exptar_{16}$	0.02	0.014	0.034	0.048		0.054
	(0.037)	(0.036)	(0.036)	(0.035)		(0.047)
Observations	656,501	548,752	640,319	938,052	446,838	663,800
R-squared	0.267	0.277	0.267	0.212	0.258	0.2
Other Trade Shock	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
CityXYear FE	Yes	Yes	Yes	Yes	Yes	Yes
YearXCohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Policies	Yes	Yes	Yes	Yes	Yes	Yes

Note: Regressions only run on sample from low-skilled families. Robust standard errors in parentheses and clustered at city of Hukou, +p<0.1, * p<0.05, ** p<0.01, *** p<0.001. Column(1) uses the treatment intensity defined before, Column(2) excludes all western areas (only 250 prefectures left), column(3) only include people with local hukou, column(4) include all people aged between 16-35 regardless of their study status, column(5) shows the results of falsification test and only include samples born before 1985. Column(6) shows the result using full specification with bootstrap standard error clustered at provincial level.

Table 2.5: Heterogeneous Effects with Different Skill Intensity

Outcomes	(1) High School	(2) High School	(3) High School	(4) Upward Mobility	(5) Upward Mobility	(6) Upward Mobility
Treat×High-Skilled ExpShock	0.0026		-0.012	0.006*		-0.006
	(0.005)		(0.01)	(0.003)		(0.01)
Treat×Low-Skilled ExpShock		-0.015***	-0.03**		-0.017***	-0.026*
		(0.007)	(0.017)		(0.006)	(0.016)
Observations	656,501	656,501	656,501	656,501	656,501	656,501
R-squared	0.151	0.151	0.266	0.266	0.21	0.21
Sample	Low-Educated	Low-Educated	Low-Educate	Low-Educated	Low-Educate	Low-Educated
Other Trade Shock	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year×Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses are clustered at the hukou city level. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6: Heterogeneous Effects: Parental Sector and Family Size

Outcomes	(1)	(2)	(3)	(4)
Panel A: High School	Parent: Industry	Parent: Agriculture	Only Child	With Siblings
Treat×ExpShock	-0.0154***	-0.0043***	-0.02***	-0.006***
	(0.006)	(0.0018)	(0.007)	(0.002)
R-squared	0.156	0.103	0.198	0.133
Panel B: Upward Mobility				
Treat×ExpShock	-0.0129***	-0.00426	-0.0173***	-0.00547**
	(0.0054)	(0.0028)	(0.007)	(0.003)
Observations	112,653	348,541	76,998	579,041
R-squared	0.264	0.324	0.211	0.281
Sample	Low-Educated	Low-Educated	Low-Educated	Low-Educated
Other Trade Shock	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
CityXYear FE	Yes	Yes	Yes	Yes
YearXCohort FE	Yes	Yes	Yes	Yes
Other Policies	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at hukou-city in parentheses. *** p<0.01, ** p<0.05, * p<0.1. $Parent : Industrial$ denotes that at least one of his/her parents work in industrial sectors, $Parent : Agriculture$ denotes that both of his/her parents work in agricultural sector. Column (3)(4) only include the samples containing their mother's information.

Table 2.7: Trade Shock and Literacy for 6-aged Children

Outcomes	(1) Literate	(2) Literate	(3) Literate	(4) Literate	(5) Literate	(6) Literate
Treat×ExpShock	-0.264**	-0.251**	-0.204*	0.159	0.135	0.136
	(0.106)	(0.105)	(0.106)	(0.147)	(0.151)	(0.158)
Constant	0.899***	0.845***	0.831***	0.933***	0.939***	0.821***
	(0.00942)	(0.0119)	(0.0504)	(0.00698)	(0.0163)	(0.0730)
Observations	50,671	50,671	50,671	17,000	16,997	16,997
R-squared	0.060	0.122	0.123	0.032	0.083	0.083
Sample	Low-Educated	Low-Educated	Low-Educated	High-Educated	High-Educated	High-Educated
Other Trade Shock	No	No	Yes	No	No	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	No	Yes	Yes
City FE	No	Yes	Yes	No	Yes	Yes

Notes: Robust standard errors clustered at household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.8: Trade Shock and Performance of Compulsory Education

VARIABLES	(1) Education performance	(2) Education performance	(3) School quality	(4) School quality	(5) Log(Edu hours)	(6) Log(Edu hours)	(7) Log(Edu expense)	(8) Log(Edu expense)
Treat×ExpShock	-1.696**	-1.738	-0.144	2.384*	-0.774	-0.503	0.617	3.595
	(0.716)	(1.288)	(0.343)	(1.383)	(0.504)	(0.658)	(1.386)	(4.110)
Observations	2,147	371	2,145	373	1,368	253	1,867	318
R-squared	0.767	0.792	0.900	0.931	0.940	0.961	0.876	0.840
Sample	Low	High	Low	High	Low	High	Low	High
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.9: Trade Shock and Parents' Absence

VARIABLES	(1) Absence	(2) Absence	(3) Absence	(4) Absence	(5) Absence	(6) Absence
Treat×ExpShock	0.158***	0.149***	0.196***	0.0803**	0.0768*	0.0396
	(0.0430)	(0.0414)	(0.0404)	(0.0343)	(0.0406)	(0.0295)
Observations	1,892,612	1,892,612	1,057,649	319,976	1,057,649	319,976
R-squared	0.120	0.120	0.139	0.099	0.138	0.100
Sample	All	All	Low-Educated	High-Educated	Low-Educated	High-Educated
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
ProvYear FE	No	No	No	No	Yes	Yes

Notes: Robust standard errors clustered at household level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

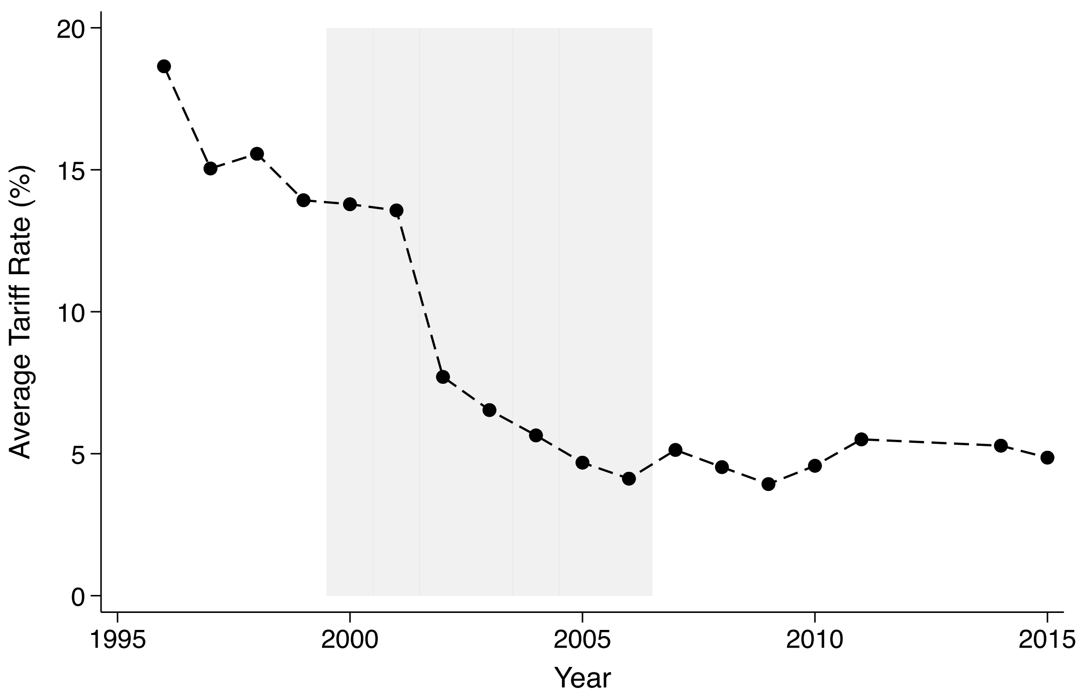


Figure 2.1: Weighted Average Import Tariff in 1996 – 2015

Notes: Each dot indicates the weighted average of industry-level import tariff in a year with industry import value as weights. The shaded area indicates the period from 2000 to 2006.

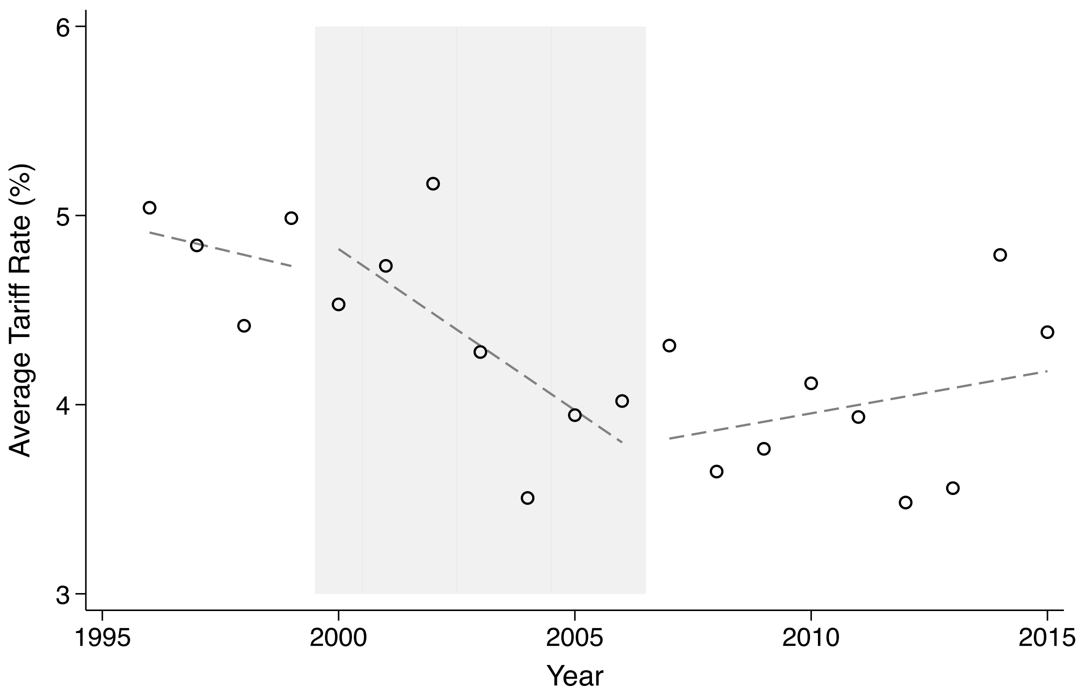


Figure 2.2: Weighted Average Export Tariff in 1996 – 2015

Notes: Each dot indicates the weighted average export tariff in a year. The export tariff is measured as the weighted average of tariffs imposed by all trading partners using trade value as weights. The shaded area indicates the period from 2000 to 2006.

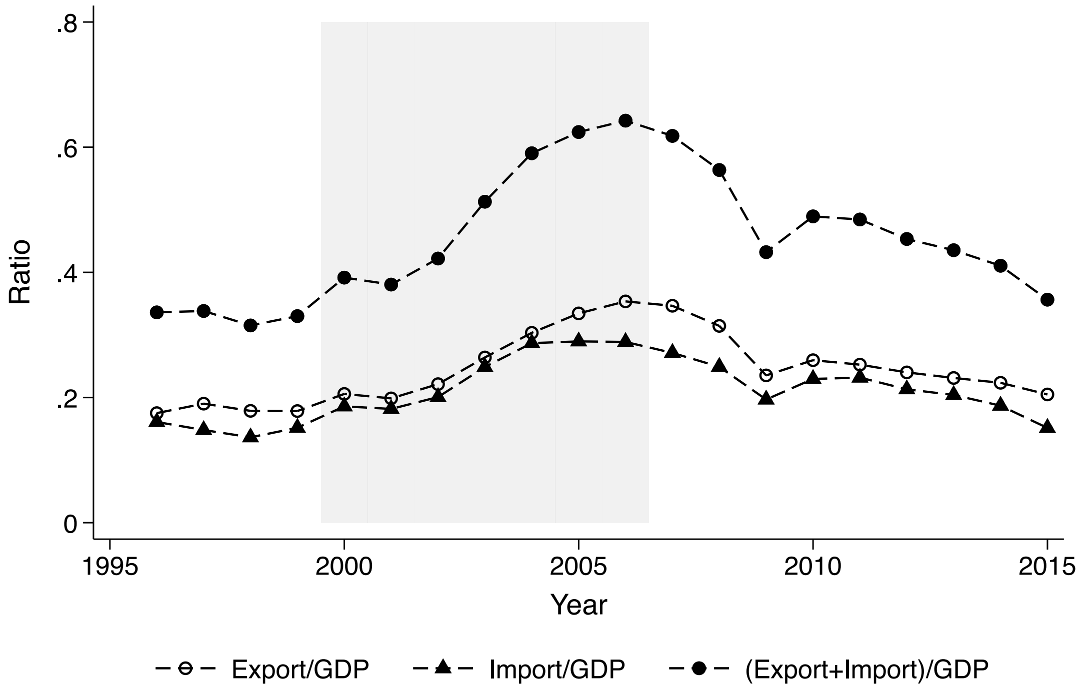
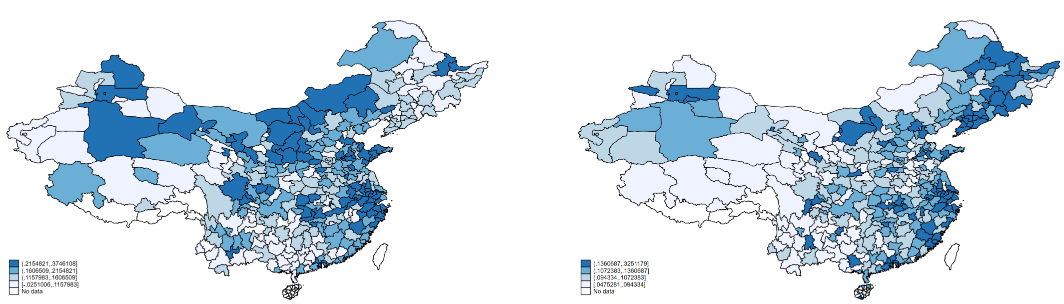


Figure 2.3: Trade on GDP in 1996 – 2015

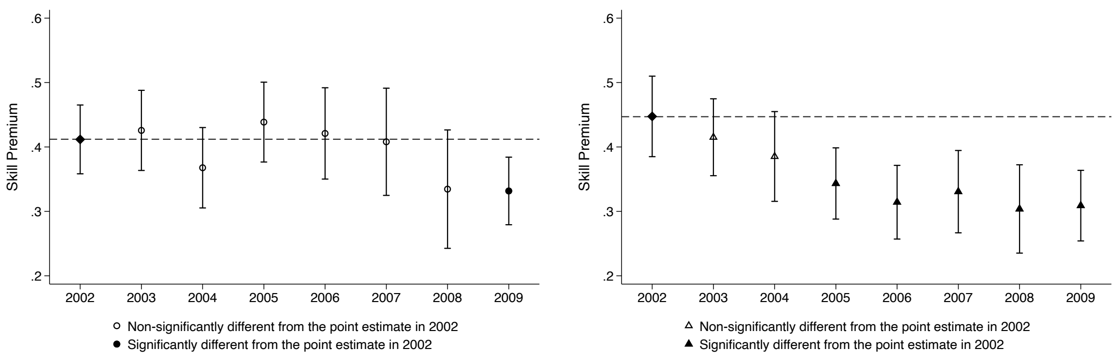
Notes: The shaded area indicates the period from 2000 to 2006.



A.Upward Mobility Change B.NTR gap in 1999

Figure 2.4: The distribution of change in education upward mobility and export tariff reduction

Notes: Panel A shows the change in the proportion of families that have children getting more education than the parents between 2000 and 2010. Panel B shows the reduction of export tariffs between 2000 and 2006.

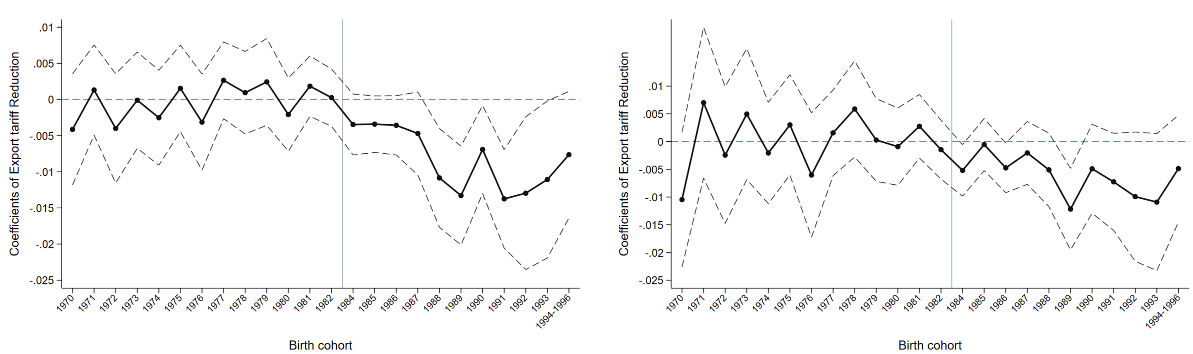


A.Above-Median Regions

B.Below-Median Regions

Figure 2.5: Skill Premium in 2002 – 2009

Notes: Panel A restrict sample to individuals in cities with an above-median level of export tariff reduction. Panel B restricts the sample to individuals in cities with a below-median level of export tariff reduction. Each marker indicates the point estimation of the coefficient β_{1t} in Equation 2.4. Vertical capped lines indicate the 95% confidence interval. The horizontal dashed line indicates the point estimate of $\beta_{1,2002}$.



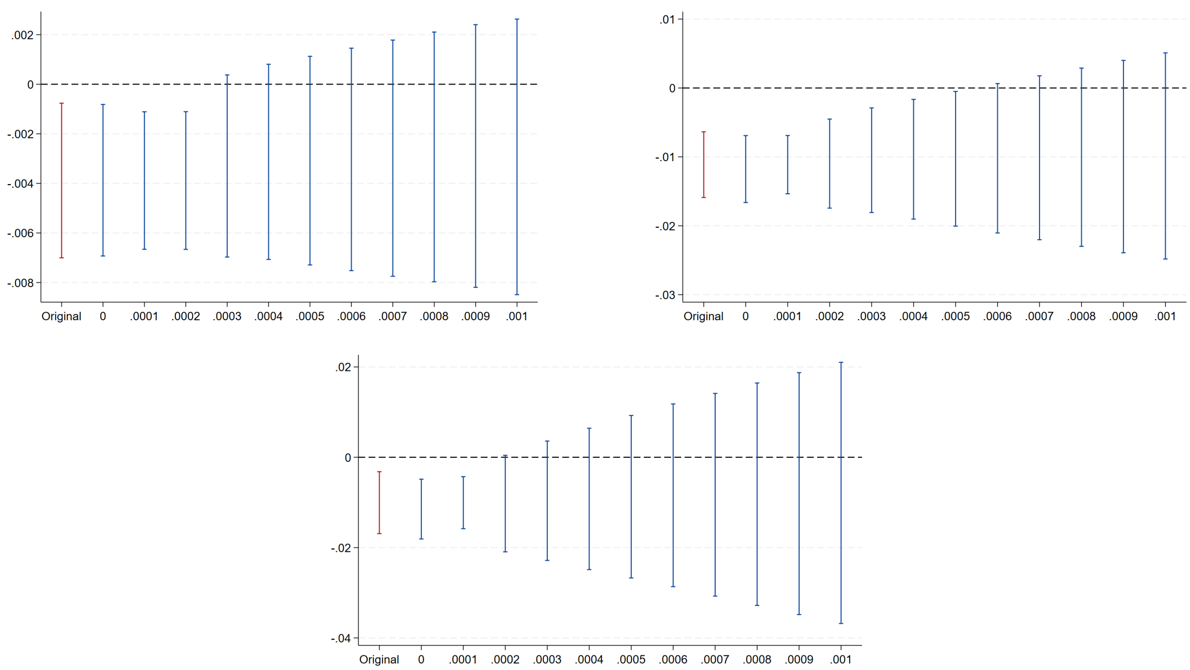
A. High school

B. Upward education mobility

Figure 2.6: Effects of Export Tariff Reduction of Different Cohorts

Notes: Both panels show results for workers from low-educated families. Dashed lines indicate the 95% confidence interval of the coefficient estimations.

Figure 2.7: Sensitivity Analysis of Export Tariff Reduction



Notes: Here we use the 2-birth year as one cohort for event study plots. We vary M from 0 to 0.5*standard error of the estimate. Upper-left Figure shows the early cohort: 1984-1987, Upper-right shows the middle cohort: 1988-1992, and the last one shows the case for late cohort.

Appendices

2.A Appendix Table

Table 2.A.1: Full Controls of the Baseline

VARIABLES	(1) High School	(2) High School	(3) High School	(4) Upward Mobility	(5) Upward Mobility	(6) Upward Mobility
Treat×ExpShock	-0.082***	-0.081***	-0.052	-0.125***	-0.138***	-0.034
	(0.037)	(0.037)	(0.067)	(0.049)	(0.05)	(0.06)
Observations	680,812	680,812	115,821	680,812	680,812	115,821
R-squared	0.197	0.196	0.312	0.116	0.114	0.216
Sample	Low-Educated	Low-Educated	High-Educated	Low-Educated	Low-Educated	High-Educated
Other Trade Shock	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cohort×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City Controls×Cohort	Yes	Yes	Yes	Yes	Yes	Yes

Notes: standard errors clustered at the city level. Controls are as the same in baseline regression, the city-level controls include the manufacture share ,log trade value per-capital in 2000 and the fraction change in college students in youth during 2000-2005. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.2: Results of the Oster Test

Dependent Variables	Controls in the restricted set	Controls in the full set	δ
High School	Controls selected in baseline regression	All potential controls	4.28
Upward Mobility	Controls selected in baseline regression	All potential controls	2.95

Notes: Full controls include workers' hukou property, migration status, marriage status, the interaction terms of the log of trade per capita in 2000 and indicators of each birth cohort, as well as the interaction terms of change in the fraction of college students during 2000-2005 and indicators of each birth cohort.

2.B Appendix Figure

Table 2.A.3: Industry Balance Test

	(1) Share of Manufacturing	(2) Share of Low-Skilled Workers	(3) Export Value	(4) Import Value
ExpShock	-0.000*	-0.013	0.009	0.019
	(0.000)	(0.019)	(0.022)	(0.031)
R^2	0.011	0.007	0.000	0.000
N	175	175	175	175

Notes: Standard errors in parentheses are clustered at the 2-digit CIC level. All outcomes are measured in 2000. Regressions are weighted by adjusted industry employment share excluding the nontradable sectors.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.A.4: Regional Balance Tests

	(1) Log(Trade Per Capita)	(2) Share of Low-Skilled Workers	(3) Share of Female	(4) Share of Youth
ExpShock	0.217	-0.009	0.002	-0.012
	(0.132)	(0.007)	(0.002)	(0.009)
R^2	0.032	0.200	-0.018	0.093
N	183	183	183	183

Notes: Standard errors in parentheses are clustered at the 2-digit CIC level. Regressions are weighted by cities' employment share.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.A.5: Shock Summary Statistics

Statistics	(1)	(2)
Mean	-0.016	-0.114
Standard deviation	0.157	0.411
Interquartile range	0	0.316
Effective Sample Size (1/HHI)	2.8	56.3
Effective Sample Size at the 2-digit CIC level	2.77	20.8
Largest employment share at the 2-digit CIC level	0.596	0.09
Number of shocks	368	175
Number of industries	369	175
Number of 2-digit CIC groups	84	33
All industries	Y	N

Notes: All statistics are weighted by the average industry exposure shares, and the HHI is calculated at the 2-digit CIC level.

Table 2.A.6: Skill Premium and Trade Shock across Years

VARIABLES	(1) Log(wage)	(2) Log(wage)	(3) Log(wage)
HS×ExpShock	-0.122	-0.435	-0.138
	(0.256)	(0.429)	(0.341)
HS×ExpShock×Y2003	0.198	0.0251	0.339
	(0.172)	(0.388)	(0.322)
HS×ExpShock×Y2004	-0.0551	0.426	0.459
	(0.238)	(0.515)	(0.413)
HS×ExpShock×Y2005	0.180	0.474	0.506
	(0.188)	(0.422)	(0.528)
HS×ExpShock×Y2006	0.0915	0.989	0.721
	(0.191)	(0.637)	(0.553)
HS×ExpShock×Y2007	0.474**	1.042	0.734
	(0.205)	(0.631)	(0.595)
HS×ExpShock×Y2008	0.0712	0.813	0.725
	(0.275)	(0.661)	(0.602)
HS×ExpShock×Y2009	0.226	0.367	0.163
	(0.210)	(0.450)	(0.353)
Constant	8.726***	8.726***	8.845***
	(0.0119)	(0.0118)	(0.00987)
Observations	102,803	102,800	99,657
R-squared	0.199	0.216	0.355
Controls	No	No	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
City×Year FE	No	Yes	Yes

Notes: Robust standard errors are clustered at the province level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.7: Subjective Evaluation and Cognitive Skills

VARIABLES	(1) Math Score	(2) Vocabulary Score	(3) Immediate Recall	(4) Delayed Recall	(5) Number Series
Grammar Performance	0.0866	1.038***	0.149***	0.117**	0.928
	(0.0647)	(0.111)	(0.0437)	(0.0540)	(0.716)
Math Performance	0.567***	0.0896	0.0615	-0.00814	4.834***
	(0.0594)	(0.0991)	(0.0405)	(0.0506)	(0.677)
Observations	5,012	5,011	2,694	2,641	2,514
R-squared	0.429	0.374	0.093	0.044	0.181
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the city level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.A.8: Education Expense and Trade Shock

VARIABLES	(1) Log(expense on education)	(2) Log(expense on cram school)	(3) Log(HH income)	(4) Log(HH expenditure)
ExpShock	0.185	0.195	0.405***	0.366***
	(0.133)	(0.186)	(0.132)	(0.124)
Observations	83,612	45,077	95,425	95,596
R-squared	0.204	0.237	0.465	0.384
Sample	With youth	With youth	With youth	With youth
ProvYear FE	Yes	Yes	Yes	Yes

Notes: Robust standard errors are clustered at the province level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

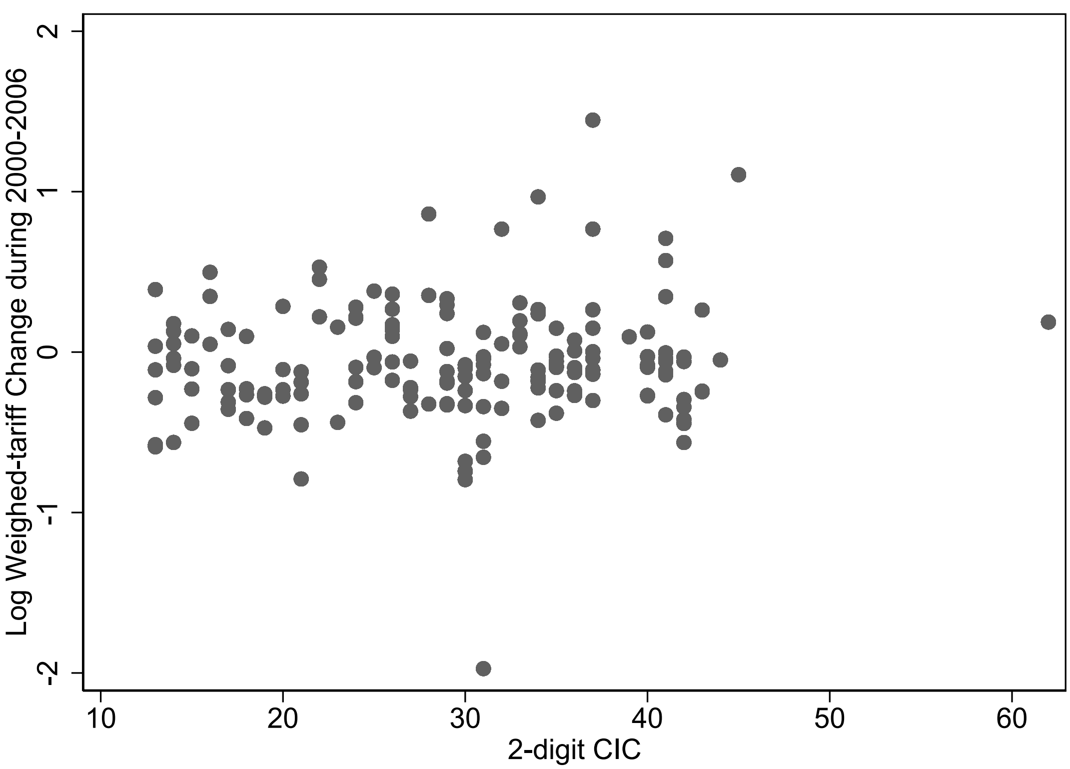


Figure B1: Export Tariff Reduction across broad sectors

Notes: Each dot represents the export tariff reduction at the 3-digit CIC level during 2000-2006 and is categorized at the 2-digit CIC level.

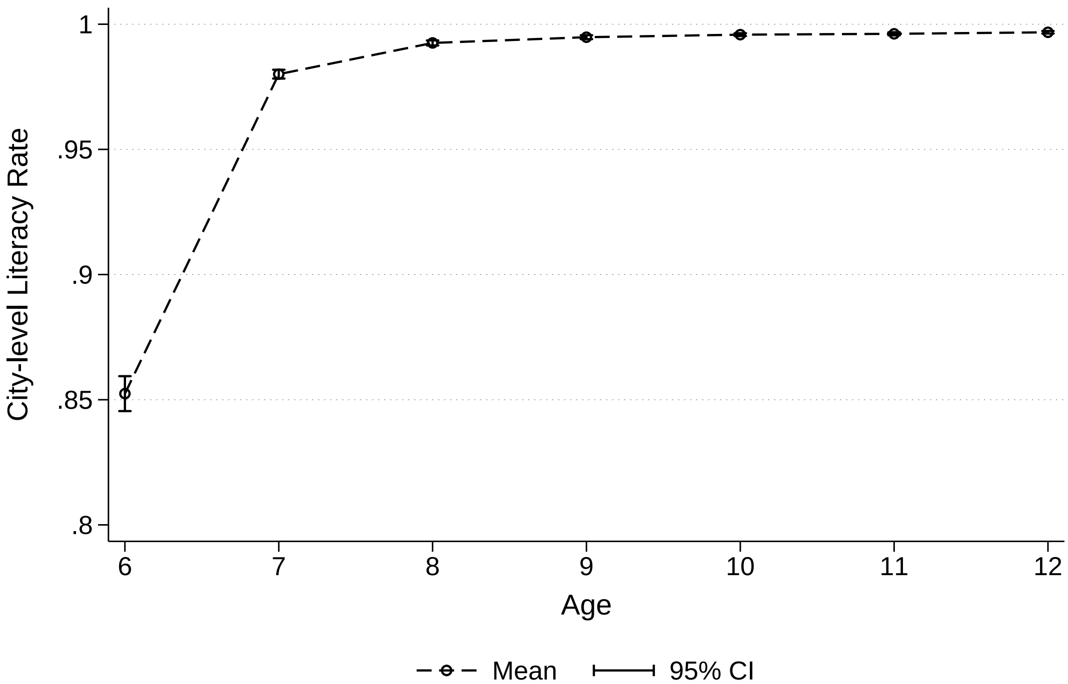
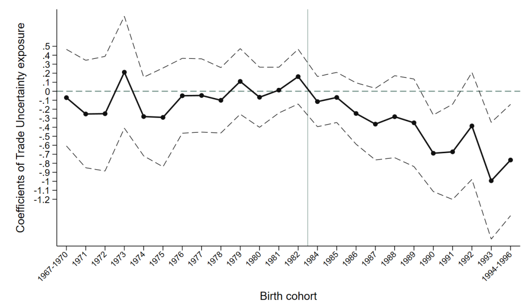


Figure B2: City-level Literacy Rate for Children Age 6 – 12 Years

Notes: Data from the pooled data set of 2000 and 2005 population census.

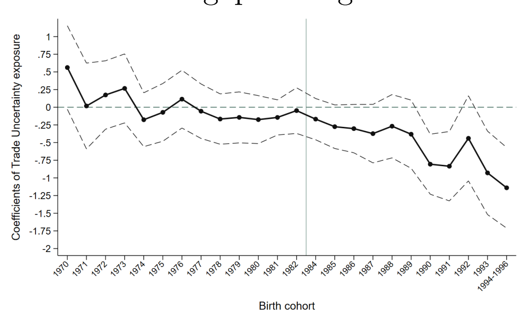
Figure B3: Event Study Plot of other Trade Shocks

Import Tariff Reduction on High School



NTRgap on High School

Import Tariff Reduction on Upward Educational Mobility



NTRgap on Upward Educational Mobility

Bibliography

Ahsan, Reshad N., and Arpita Chatterjee. 2017. "Trade liberalization and intergenerational occupational mobility in urban India." *Journal of International Economics*, 109: 138–152.

Atkin, David. 2016. "Endogenous Skill Acquisition and Export Manufacturing in Mexico." *American Economic Review*, 106(8): 2046–2085.

Bastos, Paulo, and Nicolas Santos. 2022. "Long-run effects of trade liberalisation on local labour markets: Evidence from South Africa." *The World Economy*, twec.13281.

Blanchard, Emily, and Gerald Willmann. 2016. "Trade, education, and the shrinking middle class." *Journal of International Economics*, 99: 263–278.

Blanchard, Emily J., and William W. Olney. 2017. "Globalization and human capital investment: Export composition drives educational attainment." *Journal of International Economics*, 106: 165–183.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-experimental shift-share research designs." *The Review of Economic Studies*, 89(1): 181–213.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang. 2017. "WTO Accession and Performance of Chinese Manufacturing Firms." *American Economic Review*, 107(9): 2784–2820.

Cai, Jie, and Yanhua Xu. 2022. "Intergenerational Occupational Mobility and Inequality in a Spatial Model with Trade and Immigration." Working Paper.

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna. 2024. "Difference-in-differences with a continuous treatment." National Bureau of Economic Research.

Chang, Hongqin, Xiao-yuan Dong, and Fiona MacPhail. 2011. “Labor Migration and Time Use Patterns of the Left-behind Children and Elderly in Rural China.” *World Development*, 39(12): 2199–2210.

Cheng, Wenya, and Andrei Potlogea. 2017. “Trade Liberalization and Economic Development: Evidence from China’s WTO Accession.” Society for Economic Dynamics 2017 Meeting Papers 1648.

Chetty, Raj, and Nathaniel Hendren. 2018. “The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects.” *The Quarterly Journal of Economics*, 133(3): 1107–1162.

Chetty, Raj, Nathaniel Hendren, and Lawrence F. Katz. 2016. “The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment.” *American Economic Review*, 106(4): 855–902.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. “Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States.” *The Quarterly Journal of Economics*, 129(4): 1553–1623.

Dai, Mi, Wei Huang, and Yifan Zhang. 2020. “Persistent effects of initial labor market conditions: The case of China’s tariff liberalization after WTO accession.” *Journal of Economic Behavior & Organization*, 178: 566–581.

Dai, Mi, Wei Huang, and Yifan Zhang. 2021. “How do households adjust to tariff liberalization? Evidence from China’s WTO accession.” *Journal of Development Economics*, 150: 102628.

David, H, David Dorn, and Gordon H Hanson. 2013. “The China syndrome: Local labor market effects of import competition in the United States.” *American economic review*, 103(6): 2121–68.

Dix-Carneiro, Rafael, and Brian K. Kovak. 2017. "Trade Liberalization and Regional Dynamics." *American Economic Review*, 107(10): 2908–2946.

Duflo, Esther. 2001. "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment." *American Economic Review*, 91(4): 795–813.

Erten, Bilge, and Jessica Leight. 2021. "Exporting Out of Agriculture: The Impact of WTO Accession on Structural Transformation in China." *The Review of Economics and Statistics*, 103(2): 364–380.

Facchini, Giovanni, Maggie Y. Liu, Anna Maria Mayda, and Minghai Zhou. 2019. "China's "Great Migration": The impact of the reduction in trade policy uncertainty." *Journal of International Economics*, 120: 126–144.

Fan, Jingting. 2019. "Internal Geography, Labor Mobility, and the Distributional Impacts of Trade." *American Economic Journal: Macroeconomics*, 11(3): 252–288.

Fan, Yi, Junjian Yi, and Junsen Zhang. 2021. "Rising Intergenerational Income Persistence in China." *American Economic Journal: Economic Policy*, 13(1): 202–230.

Francesconi, Marco, and Cheti Nicoletti. 2006. "Intergenerational mobility and sample selection in short panels." *Journal of Applied Econometrics*, 21(8): 1265–1293.

Furceri, Davide, Swarnali A Hannan, Jonathan D Ostry, and Andrew K Rose. 2022. "The Macroeconomy After Tariffs." *The World Bank Economic Review*, 36(2): 361–381.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik instruments: What, when, why, and how." *American Economic Review*, 110(8): 2586–2624.

Grieco, Paul L.E., Shengyu Li, and Hongsong Zhang. 2019. "Input Prices, Productivity and Trade Dynamics: Long-run Effects of Liberalization on Chinese Paint Manufacturers." *SSRN Electronic Journal*.

Hansen, Mette Halskov, and T. E. Woronov. 2013. "Demanding and resisting vocational education: A comparative study of schools in rural and urban China." *Comparative Education*, 49(2): 242–259.

Heckman, James, and Rasmus Landersø. 2021. "Lessons from Denmark about Inequality and Social Mobility." National Bureau of Economic Research w28543, Cambridge, MA.

Heckman, James, and Stefano Mosso. 2014. "The Economics of Human Development and Social Mobility." National Bureau of Economic Research w19925, Cambridge, MA.

Heckman, James J. 2008. "Role of Income and Family Influence on Child Outcomes." *Annals of the New York Academy of Sciences*, 1136(1): 307–323.

Jacoby, Hanan G., and Emmanuel Skoufias. 1997. "Risk, Financial Markets, and Human Capital in a Developing Country." *The Review of Economic Studies*, 64(3): 311.

Jensen, Robert. 2000. "Agricultural Volatility and Investments in Children." *American Economic Review*, 90(2): 399–404.

Khanna, Gaurav, Kevin Shih, Ariel Weinberger, Mingzhi Xu, and Miaojie Yu. 2020. "Trade Liberalization and Chinese Students in US Higher Education." *SSRN Electronic Journal*.

Kim, Dong-Hyeon, Shu-Chin Lin, and Yu-Bo Suen. 2010. "Dynamic effects of trade openness on financial development." *Economic Modelling*, 27(1): 254–261.

Kovak, Brian K. 2013. "Regional Effects of Trade Reform: What is the Correct Measure of Liberalization?" *American Economic Review*, 103(5): 1960–1976.

Leight, Jessica, and Yao Pan. 2021. "Educational Responses to Migration-Augmented Export Shocks: Evidence from China." The George Washington University, Institute for International Economic Policy.

Leight, Jessica, and Yao Pan. 2023. "Educational responses to local and migration destination shocks: Evidence from China."

Li, Bingjing. 2018. "Export expansion, skill acquisition and industry specialization: evidence from china." *Journal of International Economics*, 114: 346–361.

Li, Lei. 2020. "Skill-Biased Imports, Human Capital Accumulation, and the Allocation of Talent." University of Bonn and University of Mannheim, Germany CRC TR 224 Discussion Paper Series crctr224_2020_189.

Lin, Faqin, and Cheryl X. Long. 2020. "The impact of globalization on youth education: Empirical evidence from China's WTO accession." *Journal of Economic Behavior & Organization*, 178: 820–839.

Lou, Jing, and Jie Li. 2022. "Export expansion and intergenerational education mobility: Evidence from China." *China Economic Review*, 73: 101797.

Luo, Renfu, Fang Jia, Ai Yue, Linxiu Zhang, Qijia Lyu, Yaojiang Shi, Meredith Yang, Alexis Medina, Sarah Kotb, and Scott Rozelle. 2019. "Passive parenting and its Association with Early Child Development." *Early Child Development and Care*, 189(10): 1709–1723.

Lu, Yi, and Linhui Yu. 2015. "Trade Liberalization and Markup Dispersion: Evidence from China's WTO Accession." *American Economic Journal: Applied Economics*, 7(4): 221–253.

Machin, Stephen, Sandra McNally, and Jenifer Ruiz-Valenzuela. 2020. "Entry through the narrow door: The costs of just failing high stakes exams." *Journal of Public Economics*, 190: 104224.

Mitra, Devashish, Hoang Pham, and Beyza P. Ural Marchand. 2022. "Enhanced Intergenerational Occupational Mobility Through Trade Expansion: Evidence from Vietnam." *SSRN Electronic Journal*.

Nicoletti, Cheti, Kjell G. Salvanes, and Emma Tominey. 2023. "Mothers Working during Preschool Years and Child Skills: Does Income Compensate?" *Journal of Labor Economics*, 41(2): 389–429.

Oster, Emily. 2019. "Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics*, 37(2): 187–204.

Pierce, Justin R., and Peter K. Schott. 2016. "The Surprisingly Swift Decline of US Manufacturing Employment." *American Economic Review*, 106(7): 1632–1662.

Rambachan, Ashesh, and Jonathan Roth. 2023. "A more credible approach to parallel trends." *Review of Economic Studies*, 90(5): 2555–2591.

Roth, Jonathan. 2022. "Pretest with caution: Event-study estimates after testing for parallel trends." *American Economic Review: Insights*, 4(3): 305–322.

Shahbaz, Muhammad. 2012. "Does trade openness affect long run growth? Cointegration, causality and forecast error variance decomposition tests for Pakistan." *Economic Modelling*, 29(6): 2325–2339.

Wei, Q.W., J.X. Zhang, R.W. Scherpbier, C.X. Zhao, S.S. Luo, X.L. Wang, and S.F. Guo. 2015. "High prevalence of developmental delay among children under three years of age in poverty-stricken areas of China." *Public Health*, 129(12): 1610–1617.

Wu, Wenbin, and Wei You. 2020. "The Welfare Implications of Internal Migration Restrictions: Evidence from China." Social Science Research Network SSRN Scholarly Paper ID 3637557, Rochester, NY.

Yue, Ai, Yaojiang Shi, Renfu Luo, Boya Wang, Ann Weber, Alexis Medina, Sarah Kotb, and Scott Rozelle. 2019. "Stimulation and Early Child Development in China: Caregiving at Arm's Length." *Journal of Developmental & Behavioral Pediatrics*, 40(6): 458–467.

Zhang, Hongliang, Jere R. Behrman, C. Simon Fan, Xiangdong Wei, and Junsen Zhang. 2014. "Does parental absence reduce cognitive achievements? Evidence from rural China." *Journal of Development Economics*, 111: 181–195.

Zhao, Qiran, Xiaohua Yu, Xiaobing Wang, and Thomas Glauben. 2014. "The impact of parental migration on children's school performance in rural China." *China Economic Review*, 31: 43–54.

Jingxuan (Gemma) Du

Room 305, Moynihan Institute of Global Affairs, Syracuse University
Ph.D. Candidate in Economics | 315-450-4368 | jdu115@syr.edu
Website: https://sites.google.com/view/dujingxuan/home

EDUCATION

Syracuse University — Maxwell School
Ph.D. in Economics — *8/2019-8/2024(expected)*

Renmin University of China — School of Labor and Human Resources
Master in Labor Economics — *9/2017-6/2019*

Beihang University — School of Humanities and Social Science
B.A. in Economics — *9/2013-6/2017*

REFERENCES

Professor Devashish Mitra
Professor and Chair
Economics Department
Syracuse University
✉ dmitra@syr.edu

Professor Alexander Rothenberg
Assistant Professor
Economics Department
Syracuse University
✉ adrothen@syr.edu

Professor Ryan Monarch
Assistant Professor
Economics Department
Syracuse University
✉ rpmonarc@syr.edu

Professor Zhong Zhao
Dean and distinguished Professor
School of Labor and Human Resources
Renmin University of China
✉ zhao.zhong@ruc.edu.cn

RESEARCH INTERESTS

Urban Economics, International Trade and Labor Economics

RESEARCH

Internal Migration, Structural Transformation and Intergenerational Education Mobility: A Quantitative Analysis of China

This paper builds an dynamic overlapping generation spatial equilibrium model with intergenerational educational transmission to understand the role of rural-urban migration in influencing structural transformation and inequality in China. I estimate the model parameters and find that allowing all parents to move with their children induces structural change and increases welfare, primarily by improving educational mobility. I find that reducing migration costs narrows the overall welfare gap between skill groups, stimulates structural transformation, and significantly improves educational mobility, though at the cost of increased spatial inequality.

Does Trade Liberalization promote Intergenerational Education Mobility in China? (preliminary draft) with Li Zhang, The Chinese University of Hong Kong

This study examines the impact of trade liberalization on intergenerational education mobility, focusing on China's accession to the WTO. The negative impact of export tariff reduction on educational outcomes is greater for low-educated family children than for high-educated family children, reducing intergenerational education mobility. Estimations of intergenerational education elasticity also support this finding. This study proposes that the opportunity cost of education alone cannot explain the results and documents another non-negligible mechanism: parents reduce their time and effort on children's education to take new job opportunities and earn a higher income, negatively affecting early childhood development.

The Benefits and Costs of Motorization: Evidence from Jakarta (preliminary draft) with Alexander D. Rothenberg, Syracuse University

We use a quantitative spatial general equilibrium model to study how rising motorization in Jakarta impacts welfare, inequality, and urban spatial structure. We calibrate the model with high quality data on commuting flows, travel times, and vehicle ownership from Greater Jakarta, one of the world's largest agglomerations with some of the worst traffic. Counterfactual simulations suggest that reducing vehicle ownership costs would lead to increased welfare, reduce segregation, but also increase inequality.

A Curse or a Blessing: The Long-run Effects of the Soviet Union Aid Program to China (preliminary draft) with Zhong Zhao, Renmin University of China

This paper studies the influence of a heavy-industrial oriented assistance on modern private economic development in China, based on the context of Soviet Union's assistance in China in 1950s. We analyze multiple industrial and economic censuses spanning 80 years and construct a comprehensive industry-city level dataset. We find that the 156-project program reduces the entrepreneurship in modern China using an IV strategy. The results also demonstrate that the program hinders modern entrepreneurship through various channels, including a reduction in competition, increased institutional costs, and higher local wages. The negative impacts are relatively smaller in larger, denser cities, or those with higher administrative levels. We also find inter-industry spillovers have a positive effect on entrepreneurship in the service sector, as well as on local wages across different industries. Positive spatial spillovers encourage entrepreneurs to relocate to neighboring areas, resulting in an uncertain overall impact on the aggregate economy.

CONFERENCES AND SEMINARS

Renmin University of China/GLO Annual Conference **Oct/2018**

Mentoring Workshop for Women at Boston University **Sep/2021**

Chinese Economic Society(CES) North American Conference **Mar/2023**

98th Western Economic Association International **1/July/2023-7/July/2023**

TEACHING EXPERIENCE

Teaching Assistant for Chinese Economy **9/2020-5/2021**

- Responsible for Grading, designing homework holding office hour and laboratory class

Teaching Assistant for Introductory Macroeconomics **1/2022-5/2022**

- Hold office hours and laboratory classes

RESEARCH EXPERIENCE

The Welfare Effects of Motorization: Evidence from Jakarta **2022-2023**

- Research Assistant for Prof. Alexander Rothenberg, Syracuse University
- Helped develop the model, clean and organize data, implemented reduced-form analysis

Patent Network Analysis **10/2020-5/2021**

- Research Assistant for Prof. Mengxiao Liu, Syracuse University
- Used Python to clean patent data of PATSTAT and conducted network analysis

Institute of World Economics and Politics **3/2018-5/2019**

- Research Assistant
- Collected and analyzed data, developed empirical strategy to casually identify the impacts of OFDI from China on host country's political stability

China Academy of Information and Communications Technology3/2016-5/2017

- Research Assistant
- Collected and analyzed data on Made in China 2025focusing on supply chain analysis of new-energy cars. Prepare slides and draft policy reports.

WORKING EXPERIENCE

Internship at Guotai Junan Securities Co., Ltd, Beijing **9/2017-1/2018**

- Wrote company financial analysis report and daily report. Worked in a team and conducted industrial development analysis.

Internship at Tencent Research Center, Beijing **11/2018-5/2019**

- Wrote white-paper book of cultural industry, tracking and writing latest analysis report for Blockchain industry.

SCHOLARSHIPS

Graduate Excellence & National Scholarship	**2019**
Graduate Assistantship, Syracuse University	**2020-2023**
Graduate Fellowship, Syracuse University	**2019-2020, 2023-2024**

SKILLS

Programming: STATA, MATLAB, Python, R, QGIS, LATEX
Language: Mandarin (Native), English(fluent)