Intergenerational Occupational Mobility and Inequality in a Spatial Model with Trade and Immigration

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Abstract

We combine spatial economics and intergenerational career choice to study the quantitative impacts of education reform, trade, and immigration on occupational mobility and inequality. In the counterfactual experiments using a calibrated model, we find that an education reform that grants all children the same ex-ante talent distribution generates the largest intergenerational occupational mobility and welfare gains, but, counterintuitively, enlarge income inequality. Trade liberalization deters mobility across occupations and regions and increases income inequality. An immigration reform that reduces immigration costs across regions boosts cross-regional mobility and reduces inequality dramatically but reduces intergenerational occupational mobility.

JEL Classification codes: F16 F6 J24 J62 R12

Key words: Intergenerational occupational mobility, Education reform, Trade, Immigration, Inequality, and Chinese economy

1 Introduction

The Chinese people have benefited unequally from the trade liberalization of 1978 and the accession to the WTO in 2001, and young people's geographic and family origins play a large role in how much they gain from trade. Lower institutional barriers and transportation costs related to moves across regions create more equal chances for young people to take advantage of these historic structural changes. When human capital is multidimensional, the ability to migrate opens the door not only to higher income but also to new occupations and industries, in which young people can better utilize their skill-based comparative advantages. In the 2005 Chinese Population Census, we observe that cross-regional immigration and intergenerational mobility across occupations are highly correlated: 65% of the members of the younger generation who move away from their birth region enter into occupations different from those of their fathers; in contrast, only 30%

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of the members of the younger generation who stay at their birth place change to occupations different from those of their fathers. Since regions specialize in different sectors and demand very distinct occupation bundles, many young workers need to overcome the immigration barrier in order to choose a different occupation from their parents'. It seems intuitive that the high cost of interregional immigration blocks both intergenerational occupational mobility and cross-regional mobility.

When immigration costs are relatively high, the dominant type of cross-regional migration is among workers who are highly skilled in non-RCA (relative comparative advantage) occupations in the home region; when these workers move, they also change to an occupation different from that of their parents, who work in occupations for which their home region has an RCA. When immigration costs are sufficiently low, typical cross-regional immigrants are those children who inherit talents similar to those of their parents, who move across regions to match with more productive firms, but who stay in their parents' occupations. In this case, it could be that an immigration reform would reduce occupational mobility. In general, there may not be a monotonic relation between interregional immigration costs and intergenerational occupational mobility.

Another factor that hinders intergenerational occupational and income mobility is the intergenerational transmission of human capital, in that children of higher-income parents are more likely to have greater human capital in high income occupations. Can we distinguish the impact of the intergenerational transmission of human capital on occupational mobility from that of high immigration costs? Which is more effective for promoting occupational mobility and income equality: an education reform that provides all children the same talent distribution regardless of their parents' occupations, or an immigration reform that allows workers to move to regions with the best returns to their talents?

In this paper, we emphasize the importance of studying intergenerational occupational mobility in a multiregion and multisector setting because regional job markets are segmented by immigration costs. In the closed economy the barrier to intergenerational occupational mobility consists of intergenerational skill transmission and the income loss from entering an occupation that is different from parents' occupations; but in the open economy regions are drastically different in their production patterns and occupational demands due to the specialization of trade, many children need to pay an extra cross-regional immigration cost in order to work in their desirable occupations in other regions. Additionally, when we decompose the aggregate inequality measure, there are both between/within-region and between/within-occupation inequality components in the open economy, but in the closed economy, there are between/within-occupation components only. A policy change could have different implications on aggregate welfare in the open economy and in the closed economy because of the policy's impact on the between/within-region inequality components and the labor mobility across occupations, especially when cross regional productivity gaps are the dominant factor of national income differences.

Our model combines the intergenerational transmission of multidimensional skills into a multiregional, multisector trade model to study how trade costs, immigration barriers, and the intergenerational transmission of human capital affect intergenerational occupational and income mobility. We combine the classical spatial trade model of Eaton and Kortum (2002) and Redding (2016) with Hsieh, Hurst, Jones, and Klenow (2019)-style intergenerational human capital transmission and interregional immigration. We outline the occupations and regional choices of heterogeneous individuals in the presence of immigration costs, trade costs, and heterogeneous firms. Then, we calibrate the model using data from the 2005 China Population Census and parameters from Tombe and Zhu (2019) and Hsieh, Hurst, Jones, and Klenow (2019). Finally, we conduct a counterfactual analysis to quantitatively study the impact of an education reform, trade liberalization, and an immigration reform on welfare, inequality measures, and intergenerational occupational mobility.

To the best of our knowledge, we are the first to estimate the intergenerational transmission of skills across parent occupations using Chinese data. We find that the children of high-income parents have higher absolute and relative innate skills for high-income occupations. For example, children from almost all family backgrounds are similarly skilled as farmers; however, the children of principals are on average 234 times more skilled as principals than the children of farmers, 134 times more skilled as clerks, and 69 times more skilled as professionals. Such a pattern of intergenerational skill transmission is one of the sources of the intergenerational transmission of income and occupation.

Last, we conduct four counterfactual experiments to demonstrate the importance of studying occupational mobility and inequality in an open economy framework.

In the first case, we equalize the intergenerational transmission of skills across parent occupations to mimic an education reform that gives children from all family backgrounds an equal ex ante distribution of endowed skills. The policy motivations of various education reforms are more often pro-equality than pro-growth. However, in our experiment, education reform's outcome turns out to be more pro-growth than pro-equality. In this experiment, children's skill endowments are more homogenous across occupations while fixing the average skill level, and workers are more indifferent regarding skills when choosing occupations. Therefore, workers can move across occupations within their home region more easily. This case produces the highest level of intergenerational occupational mobility and the highest welfare gain among all four counterfactual experiments. The welfare gain is maximized because within-region labor supply is more elastic, in that each region's RCA sectors can attract workers from all occupations without significantly increasing wages. However, total welfare inequality is even higher than in the baseline because cross-regional productivity gaps are magnified by flexible labor mobility across occupations within the region, which causes larger income differences between regions when immigration costs remain high. In summary, the education reform promotes within-region occupational mobility and income equality only, but exacerbates national level inequality in the open economy. This result contradicts Ji (2019)'s closed economy conclusion that education reform reduces inequality.

Policy instruments to implement equal education resource allocation include but not restricted to government regulations on school system and early childhood interventions. For example, Korean and Chinese government banned private off-campus tutoring centres in 1980 and 2021, respectively, to block rich kids from receiving more academic training than poor kids. Japanese government mandates teachers to rotate regularly across schools within the country and ensures all schools receive exactly the same infrastructure and equipments. Emmers, Jiang, Xue, Zhang, Zhang, Zhao, Liu, Dill, Qian, Warrinnier et al. (2021) provides a systematic review of micro level empirical studies on the importance of stimulating parenting practices at early childhood in reducing rural children's long-term skill deficit. Although the micro level evidences are convincing, the macroeconomic impact of such regulations and interventions is yet to be examined.

This counterfactual exercise helps us evaluate the macroeconomic return to education from a new perspective. Education reforms potentially can change not only the average skill level in all occupations, but also the skill skewness across occupations. Many previous literature emphasize the average skill level indexed by years of schooling, but ignore the skill dispersion across occupations probably due to lack of precise measure. In the open economy framework, skill dispersion across occupations becomes more important because it matters to labor mobility across occupations, and large labor mobility across occupations supports regional RCA sectors with ample workers, hence regions gain more from trade. This mechanism exists in the open economy only, therefore our study complements the closed economy research on return to education.

In the next two counterfactual cases, we separately reduce interregional trade costs and immigration costs across the Chinese regions. In Case 2, trade liberalization causes regions to specialize more heavily in their RCA sectors. In the regional labor market, this specialization of production causes labor demand to be concentrated on those occupational skills used intensively by the RCA sectors. Because children's human capital is highly correlated with their parents', those with parents working in RCA sectors are more likely to choose occupations used intensively by RCA sectors and stay in their home region, hence benefiting more from trade liberalization than children from families with non-RCA occupations. Without immigration opportunities, the combination of intergenerational human capital transmission and the skewing of occupational demand toward RCA sectors lowers intergenerational occupational and cross-regional mobility, increases income inequality and strengthens the correlation between parent and child incomes.

In Case 3, we reduce immigration costs across the Chinese regions. There are two types of cross-regional immigrants. The first type are children whose random talent draw is far different from their parents' when their parents work in one of their home region's RCA sectors and who choose to move to another region where their talents have higher returns. The second type are children who inherit a similar talent draw to that of their parents but who move to another region to match with a more productive firm. When immigration costs are as high as in the baseline scenario, the majority of cross-regional movers are of the first type because their gains from immigration are large enough to compensate for the high immigration costs. When immigration costs are sufficiently low, as in this counterfactual experiment, the second type becomes more common. Nevertheless, immigration reform generates more equal wages across regions than the education reform does, reduces income inequality and weakens the correlation in intergenerational income. In summary, occupational mobility is not necessarily correlated with immigration costs; the relation depends on whether the dominant type of immigrant chooses an occupation different from that of his or her parents.

In Case 4, we simultaneously reduce interregional trade costs and immigration costs, resulting in a tradeoff between large welfare gains and income inequality. From Cases 2 and 3, we see that interregional trade liberalization and immigration reform have opposite impacts on inequality and the various intergenerational mobilities. Trade liberalization by itself increases income inequality and the parent–child income correlation, while an immigration cost reform by itself reduces inequality. When the two reforms happen together, the net outcome depends on which reform dominates quantitatively. Therefore, trade liberalization does not necessarily worsen inequality as long as cross-regional immigration barriers decline sufficiently at the same time.

Overall, we learn the following from the counterfactual experiments. First, the most effective reform for increasing intergenerational occupational mobility and welfare is an education reform that gives all children equal distributions of expected endowed skill. However, when the cross-regional productivity gap is large, the education reform enlarges instead of alleviating inequality in the open economy framework. Second, the trade and immigration reforms have opposing impacts on the inequality measures, and the combined trade and immigration reform simultaneously generates large welfare gains and significant inequality reductions.

This paper is related to the following streams of literature. The first literature is on intergenerational mobility. In economics, the research on intergenerational mobility began with Becker and Tomes (1979) and Becker and Tomes (1986), which construct an altruistic utility function and provide a theoretical framework for the study of intergenerational mobility. Subsequently, a series of empirical articles have estimated the intergenerational income elasticity and have analyzed factors affecting intergenerational mobility, such as Borjas (1993), Hilger (2015), Chetty, Hendren, Kline, and Saez (2014), Becker, Kominers, Murphy, and Spenkuch (2018), Alesina, Hohmann, Michalopoulos, and Papaioannou (2019) and Corak (2013). China's market-oriented reforms have generated prominent inequality issues, and there have been an increasing number of studies on Chinese intergenerational mobility. Deng, Gustafsson, and Li (2013), Qin, Wang, and Zhuang (2016), Liu (2018), and Fan, Yi, and Zhang (2019) use micro data to estimate intergenerational income mobility in China. Among these authors, Fan, Yi, and Zhang (2019) finds that from 2010 to 2018, China's intergenerational income elasticity increased, especially among high-income and low-income individuals, while the intergenerational mobility of middle-income individuals improved.

This article is more closely related to the intergenerational occupational mobility literature. Erikson and Goldthorpe (2002) begins the sociological research on intergenerational occupational mobility. Dunn and Holtz-Eakin (2000) finds that children in the United States are more likely to be self-employed when their father is self-employed. Hellerstein and Morrill (2011) shows that 20%-30% of all children in the United States have the same occupation as their parents. In recent years, a number of papers have started to study intergenerational occupational mobility and the changes therein in developing countries. Emran and Shilpi (2011), Hnatkovska and Lahiri (2013), and Reddy (2015) study intergenerational occupational mobility in Vietnam, Nepal, and India, respectively. The above literature empirically confirms intergenerational occupational inheritance but does not discuss the theoretical reasons for it. Ahsan and Chatterjee (2015) finds that the liberalization of trade in India has increased intergenerational occupational inheritance and inequality. Liu (2018) provides empirical evidence that China's trade liberalization increases intergenerational mobility toward higher income occupations and decreases the transition to lower income occupations. More recently, Boar and Lashkari (2021) shows that in US data, children of high-income parents are more likely to choose occupations with a high level of intrinsic quality. The closest paper to our article is Ji (2019), which studies intergenerational occupational transitions. The author constructs a closed economy model of occupational choice to study the impact of cross-occupational mobility frictions on the formation of human capital and labor productivity. Our paper uses an open economy model with multiple sectors and multiple occupations. Our main question relates to the influence of reforms to education, trade and immigration barriers on inequality and intergenerational mobility. Additionally, we calibrate the intergenerational human capital transmission matrix using intergenerational cross-regional and cross-occupational migration data from the 2005 China Population Census and 2010 China Family Panel Studies.

Another literature that we build upon is spatial economics with both trade and immigration. Markusen (1983) and Norman and Venables (1995) study the relation between factor flows and commodity flows. Iranzo, Susana, Peri, and Giovanni (2009), Xu (2014) and Hatzigeorgiou and Lodefalk (2016) explore the impact of changes in immigration costs on individuals with different skill levels and their influence on trade volume. Caliendo, Opromolla, Parro, and Sforza (2017) find that the order in which trade costs and immigration costs fall affects the original and new EU member states differently and that that order has different effects on individuals with different skill levels. Fan (2019) quantitatively estimates that the rise in China's international trade has increased domestic income inequality, especially interregional inequality, which accounts for 75% of the total inequality. Poncet (2006) shows that although the cost of labor mobility in China is high, it has gradually been declining. Labor market institutions have a significant impact on labor mobility. One of the studies most closely related to our paper is Tombe and Zhu (2019), the authors construct a spatial structural model to study the impact of the decline in trade costs and immigration costs on labor productivity. Sieg, Yoon, and Zhang (2020) embodies a new mechanism that hukou system affect intergenerational mobility in their spacial OLG model: when hukou system are eliminated, children from new migrant families can enjoy higher quality education in local public schools, instead of being sent back to low-quality schools in their hometowns.

The next literature related to this paper is on career choices and income inequality. For example, our theoretical model is based on the career choice model in Roy (1951) and Hsieh, Hurst, Jones, and Klenow (2019). Last, we learn from the following mixture of studies. Zhu (2012), Xie and Zhou (2014) and Xu and Xie (2015), among others, find that income inequality is the main social issue in China. Parro (2013), Tombe (2015) and Bernard, Eaton, Jensen, and Kortum (2003), among others, estimate a productivity dispersion parameter. Conceicao and Ferreira (2000) introduces the Theil index to measure income inequality. Young (2013) and Chan (2010) explain the history, function and recent status of the Chinese household registration system.

2 Model

In this section, we build a spatial equilibrium model based on Eaton and Kortum (2002), Redding (2016), Tombe and Zhu (2019), Hsieh, Hurst, Jones, and Klenow (2019), and Ji (2019). There are two generations, father and child, distributed across $N+1$ regions. N is the number of regions in China, and the rest of the world is considered 1 region. Each region has G sectors, and each sector hires human capital from O occupations as a production input. In this article, individuals can move within the country across regions but not across country borders, and goods can move across region and country borders.

We denote the father's occupation as i and his child's occupation as j; $i, j \in \mathbb{O}$. $\mathbb{O} = (1, 2, ..., O)$ is the set of occupations used in production in all sectors. n is the location of the father's workplace and the home region of the child. m is the place to which the child decides to move; $n, m \in \mathbb{N} = (1, 2, ..., N+1)$. $\mathbb{G} = (1, 2, ..., G)$ is the set of sectors.

The share of the father's generation working in occupation i in region n is f^n, where $\sum_{i\in\mathbb{O},n\in\mathbb{N}} f_i^n = 1$ and $n, m \in \mathbb{N}$. Every individual has a unique set of occupational skills. Both innate talent and acquired human capital contribute to the formation of occupational skill. Innate talent is an O-dimensional idiosyncratic random draw. Children choose their region and occupation conditional on their innate endowment and regional–occupational mobility costs. Firms have heterogeneous productivities in every region–sector. Flows of goods between sectors and regions are subject to trade costs. The labor market in each region–occupation is perfectly competitive.

2.1 Worker's Occupational and Regional Choice

Each worker has one child and survives for one period. Each period consists of two stages. The first stage is the juvenile period, in which a worker who chooses region m and occupation j and was born of a father in region n and occupation i (type ni, mj) accumulates human capital h_{ij}^{nm} by investing in schooling time s_{ij}^{nm} and educational expenses e_{ij}^{nm}, which are input into a Cobb-Douglas production function. The worker becomes an adult in the second stage; she/he works and earns an income to pay for her/his education and final consumption goods.

$$h_{ij}^{nm} = (s_{ij}^{nm})^{\varphi_j} (e_{ij}^{nm})^{\eta}. \tag{1}$$

In the above equation, φ_j is the contribution of the occupation j-specific time investment to human capital accumulation, and η is the contribution of education expenditure to human capital production. Each individual with a father in occupation i is born with an innate talent for each occupation $\epsilon_i = (\epsilon_{i1}, \epsilon_{i2}, ..., \epsilon_{iO})$, the value of which is an idiosyncratic draw that is independent and identically distributed across individuals. The distribution of innate talent in each origin region n and occupation i is public information. A child who is born of a father in occupation i draws talent vector $\boldsymbol{\epsilon_i}$ from a multivariate *Fréchet* distribution[1].

$$\mathbb{P}(\epsilon_{ij} < a) = \exp(-T_{ij}a^{-\theta}). \tag{2}$$

T_{ij} measures the strength of the intergenerational transmission of human capital from a father in occupation i to a child in occupation j. If T_{ij} is drastically heterogeneous across ij pairs and income dependent, for example, T_{ij} is larger for high income child occupation j, when father occupation i also has high income, then intergenerational income and occupation are highly correlated, hence dispersion in intergenerational skill transmission produces large inequality and low social mobility. In the labor market, the uneven T_{ij} across ij pairs generates unbalanced skills across occupations, which means a low substitutability between occupations. In an open economy, the low substitutability between occupations prevents workers from moving to a region's comparative advantage sectors, hence restricts aggregate welfare gain from trade. θ governs the dispersion of occupational skills and the elasticity of substitution between occupations. A higher value of θ corresponds to a smaller skill dispersion and higher substitutability between occupations, because workers are more indifferent between occupations.

A key difference from Sieg, Yoon, and Zhang (2020) is that we assume school qualities are homogenous across regions, the child's skill distribution depends on parent's occupation only. For example, when a farmer's son migrates to another region and becomes a machine operator in a manufacturing sector, the farmer's grandson will draw a random skill vector from a machine operator's son's distribution, instead of a farmer's son's distribution. When i is farmer and j belongs to other occupations, the low values of T_{ij} partially capture the quality gaps between rural and urban schools.

In the region m, occupation j labor market, a worker from region n with a father in occupation i, human capital h_{ij}^{nm}, and talent draw $\epsilon_i j$ earns income

$$I_{ij}^{nm}(\epsilon_{ij}) = w_j^m h_{ij}^{nm} \epsilon_{ij}, \tag{3}$$

where w_j^m is the effective labor wage per unit in region m and occupation j. The worker's net income after deducting the intergenerational occupational and regional immigration cost is

$$NI_{ij}^{nm}(\epsilon_{ij}) \equiv \mu_{ij}^{nm} I_{ij}^{nm}(\epsilon_{ij}) = \mu_{ij}^{nm} h_{i,j}^{nm} w_j^m \epsilon_{ij}, \tag{4}$$

where $1 - \mu_{ij}^{nm}$ is the share of income lost from intergenerational occupational and regional mobility, which is determined by factors such as the household registration system (hukou) that blocks immigrants' access to local public education and medical services, cultural differences, transportation costs, the preference to be around relatives and friends, occupational training sys-

[1]See Lind and Ramondo (2018) for details about multivariate *Fréchet* distributions.

tems and other factors that prevent the acquisition of human capital or entry into the labor market. In Sieg, Yoon, and Zhang (2020), hukou prohibits immigrant's children from high quality local schools, while we assume that immigrants' children need to pay higher tuition fee than local children, for example many immigrants' children go to more expensive private schools or pay extra fees to public schools, which is reflected as lower μ_{ij}^{nm} in the model.

A type (ni,mj) worker spends her/his net income on consumer goods $c_{ij,g}^{nm}$ and repays her/his own education expenditure e_{ij}^{nm}, assuming there is an interest-free national student loan system.

$$\sum_{g \in \mathbb{G}} p_g^m c_{ij,g}^{nm} + e_{ij}^{nm} = \mu_{ij}^{nm} w_j^m \epsilon_{ij} h_{ij}^{nm}. \tag{5}$$

We assume that the individual's utility function is Cobb-Douglas and depends on consumption of final products and leisure. The utility function of a type (ni,mj) worker with talent draw ϵ_{ij} is

$$U_{ij}^{nm}(\epsilon_{ij}) = (1 - \sum_{g \in \mathbb{G}} \alpha_g) log(1 - s_{ij}^{nm}) + \sum_{g \in \mathbb{G}} \alpha_g log(c_{ij,g}^{nm}), \tag{6}$$

where α_g and $1 - \sum_{g \in \mathbb{G}} \alpha_g$ are the shares of the final good g and of leisure in individual utility, respectively.

An individual worker makes her/his choice for occupation, region, schooling time, education and consumption based on her/his family background, talent draw, and other state variables. We decompose the optimization process into a two-step backward induction process. In the first step, given a particular destination occupation m and region j, the individual chooses her/his optimal schooling duration, education expenditure input and consumption based on budget constraint eq. (5) and human capital accumulation eq. (1). Then, we can calculate the indirect utility of this regional–occupational choice mj. Individuals' optimal schooling duration turns out to be occupation specific; therefore, we denote this choice as s_j^*.

$$s_j^* = \frac{1}{1 + \frac{B}{\varphi_j}}, \tag{7}$$

where $B = \frac{(1-(\sum_{g \in \mathbb{G}} \alpha_g))(1-\eta)}{\sum_{g \in \mathbb{G}} \alpha_g}$. φ_j is the contribution of the occupation j-specific schooling duration to human capital accumulation. In the calibration section, we identify φ_j using years of education by occupation according to the above equation. Individuals' optimal education expenditure depends on immigration costs, the wage rate, their talent draw and their schooling duration.

$$(e_{ij}^{nm}(\epsilon_{ij}))^* = (\eta \mu_{ij}^{nm} w_j^m \epsilon_{ij} s_j^{\varphi_j})^{\frac{1}{1-\eta}}. \tag{8}$$

Optimal consumption depends on the wage income net of immigration costs and education expenditure.

$$(c_{ij,g}^{nm}(\epsilon_{ij}))^* = \frac{\alpha_g(1-\eta)}{\sum_{g \in \mathbb{G}} \alpha_g} \frac{\mu_{ij}^{nm} I_{ij}^{nm} \epsilon_{ij}}{p_g^m}. \tag{9}$$

Substituting eq. (8) and eq. (7) into eq. (1), we derive the indirect utility as

$$(U_{ij}^{nm}(\epsilon_{ij}))^* \propto \mu_{ij}^{nm} V_j^m (1 - s_j^*)^B \epsilon_{ij}, \tag{10}$$

where

$$V_j^m = \frac{\eta^\eta w_j^m s_j^{\varphi_j}}{\prod_{g \in \mathbb{G}} (p_g^m)^{\frac{\alpha_g(1-\eta)}{\sum_{g \in \mathbb{G}} \alpha_g}}}. \tag{11}$$

In the second step, an individual chooses the region–occupation that offers the greatest indirect utility after drawing her/his talent vector $\boldsymbol{\epsilon}$.

$$\max_{m \in \mathbb{N}, j \in \mathbb{O}} (U_{ij}^{nm}(\epsilon_{ij}))^*. \tag{12}$$

We denote the intergenerational occupation and region transition matrix as $P = \left[p_{ij}^{nm}\right]_{O^2 \times N^2}$, where p_{ij}^{nm} represents the probability that a child from region n with a father in occupation i chooses region m and occupation j.

$$p_{ij}^{nm} = Pr\{(m, j) = (U_{ij}^{nm}(\epsilon_{ij}))^* \geq (U_{ik}^{ns}(\epsilon_{ik}))^*, \forall s \in \mathbb{N}, \forall k \in \mathbb{O}\}, \tag{13}$$

where

$$p_{ij}^{nm} = \frac{\left(\vartheta_{ij}^{nm}\right)^\theta}{\sum_{s \in \mathbb{N}} \sum_{k \in \mathbb{O}} \left(\vartheta_{ik}^{ns}\right)^\theta} \tag{14}$$

and

$$\vartheta_{ij}^{nm} = T_{ij}^{\frac{1}{\theta}} \mu_{ij}^{nm} V_j^m \left(1 - s_j\right)^B.$$

Please see the details in Appendix 6.

p_{ij}^{nm} helps us formulate the dynamic equilibrium condition between the fathers' region–occupation distribution f_i^n and the child's region–occupation distribution f_m^j. In the steady state, where the population in every region–occupation is constant, the labor inflow of members of the young generation, who will be the parents of the next generation, to a region–occupation is equal to the outflow from that same region–occupation.

$$f_j^m = \sum_{i \in \mathbb{O}} \sum_{n \in \mathbb{N}} f_i^n p_{ij}^{nm} \tag{15}$$

Note that eq. (15) holds only in the steady state, this equation does not intend to capture the flow from farmer to non-farmer occupations during the process of structure change, because this model is a static open economy model with heterogenous workers and occupational and regional choice. The driving force for workers to move across occupations and regions is heterogenous personal skill endowment different from that of their parents, instead of changing relative prices between sectors or shifting consumer demand across sectors, as required in the dynamic closed economy structural change models. To address the concern that China was still on the transition path from agriculture to manufacturing and service in 2005, and that labor inflow into and outflow from a specific region–sector may not be equal, we check eq. (15) in the immigration data across 48 domestic region–sectors and confirm that the correlation between the two sides of this equation is as high as 97.7%.

2.2 Aggregation by Region and Occupation

Now, we aggregate the individual workers' labor supply and consumption demand by region and occupation. The total supply of human capital for occupation j in region m H_j^m is

$$H_j^m = \sum_{n \in \mathbb{N}} \sum_{i \in \mathbb{O}} f_i^n p_{ij}^{nm} \int^{\infty} [h_{ij}^{nm} \epsilon_{ij}^{nm}]. \tag{16}$$

We can rewrite this as

$$H_j^m = \Phi_j^m \left(w_j^m \right)^{\left(\frac{\eta}{1-\eta} \right)}, \tag{17}$$

where

$$\Phi_j^m = \left(\eta^\eta s_j^{\varphi_j} \right)^{\frac{1}{1-\eta}} \sum_{n = \in \mathbb{N}} \sum_{i \in \mathbb{O}} f_i^n p_{ij}^{nm} \left(\mu_{ij}^{nm} \right)^{\left(\frac{\eta}{1-\eta} \right)} \left(\frac{T_{ij}}{p_{ij}^{nm}} \right)^{\frac{1}{\theta(1-\eta)}} \Gamma \left(1 - \frac{1}{\theta \left(1 - \eta \right)} \right) \tag{18}$$

Similarly, total income is denoted I_{ij}^{nm}, and net income NI_{ij}^{nm} for all workers who choose to work in region m and occupation j is

$$NI_j^m = \sum_{n \in \mathbb{N}} \sum_{i \in \mathbb{O}} f_i^n p_{ij}^{nm} NI_{ij}^{nm} \tag{19}$$

or

$$NI_j^m = \sum_{n \in \mathbb{N}} \sum_{i \in \mathbb{O}} f_i^n p_{ij}^{nm} \left(\eta^\eta \mu_{ij}^{nm} w_j^m s_j^{\varphi_j} \right)^{\frac{1}{1-\eta}} \left(\frac{T_{ij}}{p_{ij}^{nm}} \right)^{\frac{1}{\theta(1-\eta)}} \Gamma \left(1 - \frac{1}{\theta \left(1 - \eta \right)} \right). \tag{20}$$

Last, the total consumption expenditure of workers in region m is equal to their net income minus their education expense.

$$X^m = (1 - \eta) \sum_{j \in \mathbb{O}} NI_j^m, \tag{21}$$

and region m's total consumption expenditure on good g is

$$X_g^m = \frac{\alpha_g}{\sum_{g \in \mathbb{G}} \alpha_g} X^m. \tag{22}$$

See Appendix 6 for details.

2.3 Production and Trade

The final product $g \in \mathbb{G}$ is composed of a continuum of horizontally differentiated intermediate products $y_g^n(v)$, $v \in [0,1]$. A perfectly competitive firm produces good g using CES technology

$$Y_g^n = \left(\int_0^1 \left(y_g^n(v) \right)^{\frac{\delta-1}{\delta}} dv \right)^{\frac{\delta}{\delta-1}},$$

where δ is the constant elasticity of substitution between varieties. $y_g^n(v)$ maybe sourced from local producers or imported. Intermediate goods are produced by monopolistically competitive firms using different sets of occupations. A firm in region n with productivity z has the following production function.

$$y_g^n(z) = z \prod_j \left(H_{jg}^n \right)^{\gamma_{jg}},$$

where γ_{gj} are the g sector-specific input shares of the human capital in occupation j, and $\sum_j \gamma_{gj} = 1$. Following Eaton and Kortum (2002), we assume that z is an i.i.d. random draw from a *Fréchet* distribution with CDF

$$F_g^n(z) = exp\left\{ -A_g^n z^{-\kappa} \right\}.$$

The shape parameter κ is common across all regions and sectors, both in China and abroad. A_g^n measures the overall productivity level in region n for good g.

$p_g^{nm}(z)$ is the price of product g produced in region n and purchased by buyers in region m. Prices equal marginal costs in a perfectly competitive market. A firm in sector g and region n with productivity z charges a buyer in region m

$$p_g^{nm}(z) \propto \frac{1}{z} \tau_g^{nm} \prod_{j \in \mathbb{O}} \left(w_j^n \right)^{\gamma_{jg}},$$

where $\tau_g^{nm} \geq 1$ is an iceberg trade cost. Buyers in every region source individual varieties $y_g^n(v)$ from the lowest-cost location.

We denote π_g^{nm} as the fraction of region m's expenditure allocated to sector g goods produced in region n. Given the *Fréchet* distribution of technology, it is straightforward to show, as in Eaton and Kortum (2002), that the trade shares are

$$\pi_g^{nm} = \frac{A_g^n \left(\tau_g^{nm} \prod_j \left(w_j^n \right)^{\gamma_{jg}} \right)^{-\kappa}}{\sum_{k \in \mathbb{N}} A_g^k \left(\tau_g^{km} \prod_j \left(w_j^k \right)^{\gamma_{jg}} \right)^{-\kappa}}. \tag{23}$$

Trade share π_g^{nm}, akin to the intergenerational occupational and regional transmission probability p_{ij}^{nm}, is driven by relative marginal costs and not absolute marginal costs. Region m is more likely to buy good g from region n if the relative wage and trade costs decline or if relative productivity increases.

Final good g's price in region m is

$$p_g^m = \Upsilon \left[\sum_{k \in \mathbb{N}} A_g^k \left(\tau_g^{km} \prod_j \left(w_j^k \right)^{\gamma_{jg}} \right)^{-\kappa} \right]^{\frac{1}{-\kappa}}, \tag{24}$$

where

$$\Upsilon = \left[\Gamma \left(1 + \frac{1-\delta}{\kappa} \right) \right]^{\frac{1}{1-\delta}}.$$

The total revenue of firms in sector g in region n R_g^n equals total expenditures on this region–sector's product from across all regions and sectors.

$$R_g^n = \sum_{m \in \mathbb{N}} \pi_g^{nm} X_g^m. \tag{25}$$

Human capital input from occupation j in sector g and region n H_{gj}^n given Cobb-Douglas production is

$$w_j^n H_{jg}^n = \gamma_{jg} R_g^n, \tag{26}$$

and the total human capital input from occupation j in region n is

$$w_j^n H_j^n = \sum_{g \in \mathbb{G}} \gamma_{jg} R_g^n \tag{27}$$

2.4 General Equilibrium and Welfare

The total revenue of firms in one region–sector equals the total expenditure from all regions and sectors and is also equivalent to the total income of the workers in the region–sector. Therefore, by substituting eq. (25) into eq. (26), we can obtain the labor income for each region–sector occupation.

$$w_j^n H_{jg}^n = \gamma_{jg} \sum_{m \in \mathbb{N}} \pi_g^{nm} X_g^m, \forall n, m \in \mathbb{N}, j \in \mathbb{O}. \tag{28}$$

Hence, the labor market clearing condition by region–occupation is

$$\sum_{g \in \mathbb{G}} H_{jg}^n = H_j^n, \forall n \in \mathbb{N}, j \in \mathbb{O}. \tag{29}$$

In the open economy, a balance of trade condition holds for every region.

$$\sum_{m \in \mathbb{N}} \sum_{g \in \mathbb{G}} \pi_g^{nm} X_g^m = \sum_{m \in \mathbb{N}} \sum_{g \in \mathbb{G}} \pi_g^{mn} X_g^n, \forall n \in \mathbb{N}. \tag{30}$$

Definition of General Equilibrium: Given the distributions of productivity z and innate talent ϵ, the human capital accumulation equation eq. (1), intergenerational occupational and regional mobility costs $1-\mu_{ij}^{nm}$, and trade costs τ_g^{nm}, the competitive equilibrium is a set of variables: wages w_j^m, the prices of goods p_g^n, goods consumption c_{ij}^{nm}, schooling duration s_{ij}^{nm}, effective labor supply H_j^m, the migration share p_{ij}^{nm}, and the trade share π_g^{nm} for all parent regions $n \in \mathbb{N}$ and child regions $m \in \mathbb{N}$, all parent occupations $i \in \mathbb{O}$ and child occupations $j \in \mathbb{O}$ and final goods $g \in \mathbb{G}$, such that eq. (7) to eq. (30) hold.

We define aggregate welfare W as the total utility of workers in all occupations and all regions. Following Fan (2019), we measure inequality with the Theil index. Furthermore, to investigate the forces that drive the changes in the Theil index, we decompose inequality into two factors, namely, between-group and within-group inequality. In particular, we decompose the Theil index along two margins: region and occupation. Therefore, in sum, the total welfare inequality measure is decomposed into between-region, within-region, between-occupation and within-occupation components.

$$W = \sum_{n\in\mathbb{N}} \sum_{m\in\mathbb{N}} \sum_{i\in\mathbb{O}} \sum_{j\in\mathbb{O}} E(U_{ij}^{nm}(\epsilon_{ij}^{nm}))^* \tag{31}$$

or

$$W = \sum_{n\in\mathbb{N}} \sum_{m\in\mathbb{N}} \sum_{i\in\mathbb{O}} \sum_{j\in\mathbb{O}} f_i^n \left(p_{ij}^{nm}\right)^{\left(1-\frac{1}{\theta}\right)} \left(T_{ij}\right)^{\frac{1}{\theta}} \mu_{ij}^{nm} V_j^m \left(1-s_j\right)^B \Gamma\left(1-\frac{1}{\theta}\right) \tag{32}$$

The between-region, within-region, between-occupation and within-occupational decompositions of the Theil index are defined as follows.

$$Theil_{BR} = \sum_{m\in\mathbb{N}} \frac{W^m}{W} log(\frac{\overline{W^m}}{\overline{W}}),$$

$$Theil_{WR} = \sum_{m\in\mathbb{N}} \frac{W^m}{W} \sum_{j\in\mathbb{O}} \frac{\overline{W_j^m}}{\overline{W^m}} log(\frac{\overline{W_j^m}}{\overline{W^m}}),$$

$$Theil_{BO} = \sum_{j\in\mathbb{O}} \frac{W_j}{W} log(\frac{\overline{W_j}}{\overline{W}}),$$

and

$$Theil_{WO} = \sum_{j\in\mathbb{O}} \frac{W_j}{W} \sum_{m\in\mathbb{N}} \frac{\overline{W_j^m}}{\overline{W_j}} log(\frac{\overline{W_j^m}}{\overline{W_j}}),$$

where $\overline{W_j^m}$ is the average welfare among all workers in occupation j in region m, $\overline{W_j}$ is the average welfare among all workers in occupation j, and $\overline{W^m}$ is the average welfare among all workers in region m.

3 Data and Calibration

In this section, we describe the data sources and calibration process used to estimate α_g, τ_g^{nm}, γ_{jg}, s_j, ϕ_j, η, μ_{ij}^{nm}, A_g^n, T_{ij}, for $\forall m, n \in \mathbb{N}, \forall i, j \in \mathbb{O}$, κ and θ.

3.1 Data Description

We parameterize the model using Chinese data from circa 2005. Quantifying the model primarily requires the following information. As in Tombe and Zhu (2019), to estimate trade costs, we need information on trade flows and geographic distances between regions. To calibrate regional sector productivity, intergenerational occupational endowments, efficiency wages, and intergenerational occupational and regional mobility costs, we need trade shares, the intergenerational occupational and regional transition matrix, the final product shares in the utility function, the human capital input shares, schooling durations, and the returns to schooling durations.

First, we calculate China's domestic trade share and export share through the 2007 Chinese regional input–output statistics table in Zhang and Qi (2012). We use 2007 Chinese customs data to construct the Chinese trade flow with the rest of the world, and the world input–output table to construct the trade flow within the rest of world [2]. The latitude and longitude of the regional capital cities in China are taken from Google Maps. The data on the latitude and longitude of capitals around the world are derived from Mayer and Zignago (2011). Then, we estimate the spatial distance between capital cities through Google Maps. Last, based on geographic distance, we estimate interregional trade costs. Second, we use the 2007 OECD STAN database for China to calculate the shares of final goods in Chinese consumers' utility function.

Finally, we construct the intergenerational occupational transition matrix using the 2005 China Population Census, which reports child's registered hukou location, current residence, income and occupation, and her/his father's occupation and income if the father and child are registered in the same household. This information allows us to track intergenerational migration across regions and occupations as defined in the model. This census also reports individual-level schooling durations and employment sectors, which enable us to measure occupation-specific schooling durations, returns to schooling durations and sector–occupational wage shares. The caveat of this data source is that once children obtain their own hukou, they are no longer included in their parents' household hukou record. Since high-skilled workers are more likely to obtain an independent hukou than low-skilled workers, we are likely to underestimate the immigration probability for high-skilled children. To compensate for this shortcoming in the population census, we verify our results with the 2010 China Family Panel Studies (CFPS), which is not restricted by the availability of hukou information but has a much smaller sample size than the population census. There are many father region–occupation to child region–occupation immigration flows that are estimated to be zero in the CFPS but positive in the population census. Therefore, we use the average of the immigration flows from the two data sources.

[2] Quast (2013)

We divide China into eight regions: the northeast (Heilongjiang, Jilin, Liaoning and Inner Mongolia), Jingjin (Beijing and Tianjin), the north coast (Hebei and Shandong), the east coast (Shanghai, Jiangsu and Zhejiang), the south coast (Guangdong and Fujian), the central region (Shanxi, Henan, Anhui, Hubei, Jiangxi and Hunan), the northwest (Shanxi, Gansu, Qinghai, Ningxia, Inner Mongolia and Xinjiang) and the southwest (Chongqing, Sichuan, Yunnan, Guizhou and Hainan). Following the Industry Classification Standard of $GB/T4754-2002$, we divide the industries into eight sectors, such as agriculture; mining; light industry; heavy industry; the production and supply of electricity, gas and water; construction; wholesale and retail trade and transport; the storage and post industries and other services.[3] Additionally, following the $GB/T4754-2002$ standard, we divide occupations into six categories: principals, clerks and relevant personnel, professional technicians, manufacturing and transportation equipment operators and relevant personnel, commercial and service personnel, and farmers. [4] Compared with simple 2-sector 2-occupation models, the greater number of sectors allows the 8 domestic and 1 foreign regions to specialize in a larger 8-dimensional space according to their comparative advantage; similarly, the larger number of occupations gives us a more precise vision of occupational transition, beyond farmer and non-farmer occupations. The more complex specialization pattern can then deliver the social mobility relevant outcomes from trade liberalization: greater concentration of production in RCA sectors and labor demand in RCA occupations across 8 domestic regions.

We denote intergenerational mobility across Chinese regions in 2005 as $p^{nm} = \sum_{i,j\in\mathbb{O}} p_{ij}^{nm}/O^2$ in Table 8 and the intergenerational mobility across occupations as $p_{ij} = \sum_{n,m\in\mathbb{N}} p_{ij}^{nm}/N^2$ in Table 9. In Table 8, children are more likely to stay in the same occupation as their parents, except for the children of principals. Children of higher-income parents are more likely to enter other high-income occupations than children of low-income parents. In Table 9, children are most likely to stay in their home region; the central, southwest and northeast regions are the regions with the largest net outflows of members of the younger generations.

3.2 Calibration

Our calibration process follows that of Hsieh, Hurst, Jones, and Klenow (2019) and Tombe and Zhu (2019). The calibration results are shown in Table 1. η denotes the elasticity of human capital with respect to educational expenditure and is equal to the fraction of output spent on human capital accumulation. θ governs the dispersion of occupational skills. We use the same parameter values as those in Hsieh, Hurst, Jones, and Klenow (2019), that is, $\eta = 0.103$ and $\theta = 2$. $\sum_{g\in\mathbb{G}} \alpha_g$ is the share of all final goods in the utility function, and $1 - \sum_{g\in\mathbb{G}} \alpha_g$ is the share of leisure in the utility function. We set $1 - \sum_{g\in\mathbb{G}} \alpha_g = 0.59$, following Hsieh, Hurst, Jones, and Klenow (2019), so

[3]Henceforth, we abbreviate sector names as agri, mining, light-ind, heavy-ind, ele-gas-water, cons, retail-trans, and other service.

[4]Henceforth, we abbreviate the occupation names as principals, clerks, pro-techs, manu-trans operators, com-services personnel, and farmers.

the share of consumer goods in the personal utility function is 0.41.[5]

We use 2007 OECD data on China to calculate the share of final goods in the utility function. Because there is no capital in this model, the final demand for goods from sector g is household final consumption plus the final consumption of nonprofit organizations plus government consumption, the share of goods from sector g in total final consumption is final demand for goods from sector g/total final demand, and α_g is the share of total final consumption times the share of consumer goods in the utility function.

We estimate the schooling durations of different occupations based on education levels in the 2005 China Population Census data. The average schooling durations of the individuals who are principals, clerks, pro-techs, manu-trans operators, com-services personnel, and farmers are 11.091, 11.388, 11.086, 8.136, 8.601, and 5.923 years, respectively. According to Hsieh, Hurst, Jones, and Klenow (2019), s_j is equal to the average schooling duration divided by 25. Then, we use eq. (7), α_g and η to calculate the return to human capital φ_j. We assume that the share of occupation j in the inputs for sector g, γ_{jg}, does not vary over time or across regions. We use the total salary earned by workers in occupation j divided by the total salary earned by all workers in sector g in the 2005 census data to calculate γ_{jg} and report their values in Table 2. κ governs the productivity dispersion across firms and determines the sensitivity of trade flows to trade costs. Following Tombe and Zhu (2019), we set $\kappa = 4$.

3.2.1 Trade Costs

To estimate trade costs, we follow Head and Ries (2001) and back out the trade costs between region n and region m for sector g goods using only observable trade shares and the trade-cost elasticity κ following equation eq. (23). Specifically,

$$\tilde{\tau}_g^{nm} = \sqrt{\tau_g^{nm}\tau_g^{mn}} = \left(\frac{\pi_g^{nn}\pi_g^{mm}}{\pi_g^{nm}\pi_g^{mn}},\right)^{\frac{1}{2\kappa}}. \tag{33}$$

This method has a number of advantages. In particular, $\tilde{\tau}_g^{nm}$ is not affected by trade volumes or by third-party effects and applies equally well whether trade balances or not. Unfortunately, these trade cost estimates are symmetric in the sense that moving goods from n to m is as costly as moving goods from m to n. This matters, as Waugh (2010) and Tombe and Zhu (2019) demonstrate that international trade costs differ systematically depending on the direction of trade. To capture this, following Tombe and Zhu (2019) and Tombe (2015), we assume that the trade cost asymmetries are exporter-specific such that $\tau_g^{nm} = t_g^{nm}t_g^n$, where t_g^{nm} are the symmetric parts of trade costs (t_g^{nm}=t_g^{mn}) and t_g^n are country-specific export costs. Combining the above two formulas, we obtain

[5] When Hsieh, Hurst, Jones, and Klenow (2019) normalizes the share of leisure to 1, the share of all final products is 0.693, so in this model, $1 - \sum_{g \in \mathbb{G}} \alpha_g = 0.59$.

$$\tau_g^{nm} = \tilde{\tau}_g^{nm} \sqrt{\frac{t_g^n}{t_g^m}}. \tag{34}$$

Following Head and Mayer (2014), the trade costs can be expressed as

$$\ln\left(\frac{\pi_g^{nm}}{\pi_g^{mm}}\right) = S_g^n - S_g^m - \kappa \ln\left(\tau_g^{nm}\right), \tag{35}$$

where S_g^n captures any region-specific factor that affects competitiveness, such as factor prices or productivity, and τ_g^{nm} measures the trade costs.

Following Tombe and Zhu (2019), we assume that trade costs are composed of two parts: a symmetric part and an asymmetric export part. If the symmetric component is well proxied by geographic distance, then t_g^n can be estimated by

$$\ln\left(\frac{\pi_g^{nm}}{\pi_g^{mm}}\right) = \omega_g \ln(d_{nm}) + i_g^m + \rho_g^n + \varepsilon_g^{nm}, \tag{36}$$

where ω_g is the distance elasticity of trade costs in sector g, d_{nm} is the geographic distance between regions m and n, and i_g^m and ρ_g^n are sector-specific importer and exporter fixed effects. As the exporter fixed effect is $\hat{i}_g^m = -S_g^m$ and the importer fixed effect is $\hat{\rho}_g^n = S_g^n - ln(t_g^n)$, we infer the export cost as follows:

$$\ln\left(\hat{t}_g^n\right) = -\frac{\left(\hat{i}_g^n + \hat{\rho}_g^n\right)}{\kappa}. \tag{37}$$

Using the export cost estimated above and the Head–Reis index $\tilde{\tau}_g^{nm}$, we can calculate τ_g^{nm}. We refer to Mayer and Zignago (2011) for the estimation of d_{nm}.

$$d_{nm} = \left(\sum_{k\in\mathbb{N}} (\text{pop}_k \,/\, \text{pop}_n) \sum_{\ell\in m} (\text{pop}_\ell \,/\, \text{pop}_m)\, d_{k\ell}^{\theta_d}\right)^{1/\theta_d}, \tag{38}$$

where $\theta_d = 1$.

We report the population-weighted interregional trade costs and sectoral trade costs in Table 6 and Table 7. We find that the trade costs between regions have the following notable patterns. First, trade costs and distance are positively correlated. Second, the import trade costs for countries with higher levels of economic development are lower. Third, the trade costs for agriculture, mining, and light industry are lower, between 3 and 5. The commercial delivery warehouse industry has the highest trade costs, close to 21, which is nearly 7 times those of light industry; next are heavy industry, construction, and other services, which have costs between 10 and 11, nearly three times of those of light industry.

3.2.2 Other Parameters

We use a generalized method of moments to calibrate A_g^n, T_{ij}, w_j^m and μ_{ij}^{nm} by setting the child's region–occupation choice probability eq. (14), the dynamic equilibrium for the allocation of labor across regions and occupations eq. (15), trade shares eq. (23), the region–occupational human capital clearing condition eq. (27), the relative average regional–occupational income $A\bar{I}_j^m$ and relative cross-occupational income AI_{ij} in eq. (42) and eq. (44) as targeted moments. We normalize the productivity level of agriculture in the northeast to one, $A_1^1 = 1$, and the wage rate of principals in the northeast to one, $w_1^1 = 1$. In total, there are N^2O^2+$G(N+1)^2 - 1$ +$3(N+1)O - 1$ + O^2 moments and $G(N+1) - 1$+ O^2+$(N+1)O - 1$ +N^2O^2 unknowns, which means that the system is overidentified.

$$
\begin{aligned}
&\min_{A_g^n, w_j^m, T_{ij}, \mu_{ij}^{nm}} \sum_{g\in\mathbb{G}} \sum_{n\in\mathbb{N}} \sum_{m\in\mathbb{N}} \left(log\left(\pi_g^{nm}\right)^{data} - log\left(\pi_g^{nm}\right)^{model} \right)^2 \\
&+ \sum_{j\in\mathbb{O}} \sum_{m\in\mathbb{N}} (log(A\bar{I}_j^m)^{data} - log(A\bar{I}_j^m)^{model})^2 \\
&+ \sum_{i,j\in\mathbb{O}} (log(A\bar{I}_{ij})^{data} - log(A\bar{I}_{ij})^{model})^2 \\
&+ \sum_{j\in\mathbb{O}} \sum_{i\in} \sum_{n\in\mathbb{N}} \sum_{m\in\mathbb{N}} (log(p_{ij}^{nm})^{data} - log(p_{ij}^{nm})^{model})^2 \\
&+ \sum_{j\in\mathbb{O}} \sum_{m\in\mathbb{N}} (log(\sum_{i\in\mathbb{O}} \sum_{n\in\mathbb{N}} p_{ij}^{nm} f_i^n) - log(f_j^m))^2
\end{aligned}
\tag{39}
$$

.

Under the constraints that

$$\sum_{n\in\mathbb{N}} \sum_{i\in\mathbb{O}} f_i^n = 1 \tag{40}$$

and

$$\sum_{i\in\mathbb{O}} f_i^{N+1} = (3 - 0.76)/0.76. \tag{41}$$

The world labor force was 3 billion in 2005, and the share of the labor force that was in China was 0.76. Here, we define the regional–occupational average income and the regional–occupational average relative income as

$$AI_j^m = \frac{\sum_{n\in\mathbb{N}} \sum_{i\in\mathbb{O}} f_i^n p_{ij}^{nm} \Delta_{ij}^{nm} \left(w_j^m\right)^{\frac{1}{1-\eta}}}{\sum_{n\in\mathbb{N}} \sum_{i\in\mathbb{O}} f_i^n p_{ij}^{nm}} \tag{42}$$

and

$$A\bar{I}_j^m = \frac{AI_j^m}{AI_1^1}. \tag{43}$$

Similarly, the cross-occupational average income and cross-occupational average relative income are

$$AI_{ij} = \frac{\sum_{n\in\mathbb{N}} \sum_{m\in\mathbb{N}} f_i^n p_{ij}^{nm} \Delta_{ij}^{nm} \left(w_j^m\right)^{\frac{1}{1-\eta}}}{\sum_{n\in\mathbb{N}} \sum_{m\in\mathbb{N}} f_i^n p_{ij}^{nm}}, \tag{44}$$

and

$$\bar{AI}_{ij} = \frac{AI_{ij}}{AI_1^1}, \tag{45}$$

where

$$\Delta_{ij}^{nm} = \left(\eta^\eta \left(\mu_{ij}^{nm}\right)^\eta s_j^{\varphi_j}\right)^{\frac{1}{1-\eta}} \left(\frac{T_{ij}^n}{p_{ij}^{nm}}\right)^{\frac{1}{\theta(1-\eta)}} \Gamma\left(1 - \frac{1}{\theta\left(1-\eta\right)}\right). \tag{46}$$

The parameters are identified by different sets of targeted moments. The immigration probability eq. (14) and population distribution eq. (15) across region–occupation cells regulate μ_{ij}^{nm}, the trade shares eq. (23) mainly determine A_g^n, the immigration probability eq. (14) and the relative cross-occupational income AI_{ij} in eq. (42) jointly pin down T_{ij}, and w_j^m enters almost all targeted moments.

3.3 Calibration Results and Model Validation

First, we present a calibrated matrix of intergenerational skill transmission across occupations T_{ij} in Table 3. T_{ij} is interpreted as follows. Education expenditure $e_{ij}^{nm}\left(\varepsilon_j\right)$ and utility $U_{ij}^{nm}(\epsilon_{ij})$ increase in $\left(T_{ij}\right)^{\frac{1}{\theta}}$; that is, T_{ij} directly determines the match of the child's innate skills with different occupations and her/his utility in different occupations. In Table 3, we rank occupations by their average income from left to right and from top to bottom. Children from high-income parents have higher absolute innate skills for all occupations, except for farming. Moreover, we find that children from high-income parents have a higher relative comparative advantage in high-income occupations in China. For example, children from almost all family backgrounds are similarly skilled as farmers; however, the children of principals are on average 234 times more skilled as principals than the children of farmers, are 134 times more skilled as clerks, and are 69 times more skilled as pro-techs. This pattern in the intergenerational transmission of skill is a source of the intergenerational inheritance of income and occupations.

Second, we decompose the immigration cost $1-\mu_{ij}^{nm}$ by father–child occupational pair $1-\mu^{ij} = 1 - \frac{\sum_{n,m\in\mathbb{N}} f_i^n p_{ij}^{nm} \mu_{nm}^{ij}}{\sum_{n,m\in\mathbb{N}} f_i^n p_{ij}^{nm}}$ and father–child regional pair $1-\mu_{nm} = 1 - \frac{\sum_{i,j\in\mathbb{O}} f_i^n p_{ij}^{nm} \mu_{nm}^{ij}}{\sum_{i,j\in\mathbb{O}} f_i^n p_{ij}^{nm}}$. In Table 4, we find that children pay the lowest immigration costs when they are working in their home region, especially in highly economically developed areas, such as Jingjin, the east coast and the south coast. Moreover, the cost of immigration between regions is positively correlated with geographic distance. Last, when children flow to areas with high levels of economic development and high income, such as Jingjin, the east coast and the south coast, the proportional immigration cost is lower. This could be because immigration costs are fixed costs, and so the immigration cost is proportionally lower when divided by the higher income in richer regions. Table 5 shows the cost of changing occupations across generations. We find that the cost is lowest (except among principals) when the son chooses his father's occupation.

Third, we use the targeted moments and the Theil index of income inequality to validate the model. We start with the model's performance regarding the targeted moments. The panels in Figure 1 compare the data and model-implied log-scaled values of the trade shares π_g^{nm} in eq. (23), the immigration probability p_{ij}^{nm} in eq. (14), the relative average real income by father–child occupation pair ij $A\bar{I}_{ij}$, the relative average income of child by region and occupation $A\bar{I}_j^m$ defined in eq. (42), the worker distribution across region–occupation cells f_i^n in eq. (15), and the model-implied values of total revenue and total labor compensation by region–sector cell, R_j^m and $H_j^m * w_j^m$ in eq. (26); the correlations are 0.98, 0.99, 0.93, 0.97, 0.99 and 0.91, respectively.

Overall, these validation exercises confirm that the model's predictions about trade and immigration frictions are in line with the data; therefore, we are confident in our application of the model to the counterfactual analysis in the following section.

4 Counterfactual Experiments

4.1 General Practice

We run four counterfactual experiments to identify the main drivers of intergenerational occupational mobility, total welfare and inequality. In each counterfactual experiment, we adopt a hypothetical parameter value for T, τ or μ, and then we recalculate the workers' region–occupation allocation f_i^n and wage rate w_i^n in the new steady state, using the general equilibrium conditions eq. (15), eq. (29) and eq. (30) as targeted moments[6].

Once f_i^n and w_i^n are available, we can calculate the intergenerational mobility across regions and occupations using eq. (14) and income and welfare using eq. (20) and eq. (32) in the counterfactual general equilibrium. Finally, we compare the different counterfactual steady states with the baseline equilibrium—the Chinese economy in 2005—and with each other. Specifically, mobility across regions, across occupations and across region–occupation cells are defined as

$$M_{BR} = 1 - \sum_{n \in \mathbb{N}} \sum_{i,j \in \mathbb{O}} f_i^n p_{ij}^{nn},$$

$$M_{BO} = 1 - \sum_{i \in \mathbb{O}} \sum_{n,m \in \mathbb{N}} f_i^n p_{ii}^{nm},$$

and

$$M_{BRO} = 1 - \sum_{i \in \mathbb{O}} \sum_{n,m \in \mathbb{N}} f_i^n p_{ii}^{nm} - \sum_{n \in \mathbb{N}} \sum_{i,j \in \mathbb{O}} f_i^n p_{ij}^{nn} + \sum_{i,j \in \mathbb{O}} \sum_{n,m \in \mathbb{N}} f_i^n p_{ij}^{nm}.$$

We calculate the intergenerational income elasticity as the coefficient from a regression of NI_{ij}^{nm} on NI_i^n, using the population shares of child from region n with a father in occupation i moving

[6] We assume that there is no immigration between China and the rest of world (ROW); and that the ROW has no cross-occupational mobility, i.e., that the labor supply in each occupation is fixed in the ROW as in the baseline.

to region m to work in occupation j $f_i^n p_{ij}^{nm}$ as weights.

$$NI_{ij}^{nm} = IGE * NI_i^n + \psi_{NI,ij}^{nm}$$

where NI_{ij}^{nm} and NI_i^n are taken from eq. (20) and eq. (4).

We then derive the counterfactual aggregate welfare W by substituting the hypothetical values of T, τ, and μ_{ij}^{nm} and the calculated values of f_i^n, p_{ij}^{nm}, and V_j^m from the new equilibrium into eq. (32).

Last, since there are no analytical expressions for the Theil index of welfare and its decompositions, we run a simulation with 50000 *Fréchet*-distributed random talent draws $\epsilon_{ij}^{nm}(\ell)$ with scale parameter $\left(\theta\frac{T_{ij}}{p_{ij}^{nm}}\right)^{\left(\frac{1}{\theta}\right)}$ and shape parameter $\theta, \forall i, j \in \mathbb{O}, n, m \in \mathbb{N}$.

$$Theil = \sum_{i,j\in\mathbb{O}} \sum_{m,n\in\mathbb{N}} \sum_{\ell_r=1}^{50000} [f_i^n p_{ij}^{nm} \frac{U_{ij}^{nm}(\epsilon_{ij}^{nm}(\ell_r))}{W} log(\frac{U_{ij}^{nm}(\epsilon_{ij}^{nm}(\ell_r))}{W})],$$

where $U_{ij}^{nm}(\epsilon_{ij}^{nm}(\ell_r))$ is calculated using eq. (11).

4.2 Case 1: Education Reform

We set the intergenerational transmission of human capital across all father–child occupational pairs to the same value, which is the weighted average of the intergenerational transmission of human capital across all occupations in the calibrated baseline model. It is, of course, unrealistic that complete equality in education resource allocation would be achieved, but we want only to show the upper bound on the outcomes that an education reform could achieve.

$$T_{new,ij} = \sum_{i,j\in\mathbb{O}} \sum_{n,m\in\mathbb{N}} f_i^n p_{ij}^{nm} T_{ij}, \forall i, j \in \mathbb{O}$$

where f_i^n is the fathers' occupational–regional distribution and p_{ij}^{nm} is the benchmark probability of immigrating from father region–occupation cell ni to child region–occupation cell mj from 2005. This counterfactual experiment mimics an education reform that gives children from all family backgrounds an equal ex ante distribution of different endowed occupational skills. As mentioned before, the homogenous T_{ij} across ij pairs means more balanced skill distribution across occupations and higher substitutability across occupations. In the open economy, this assumption transfers into a greater labor mobility across occupations, which matters not only to inequality and social mobility but also to gain from trade, because workers can easily move to those regional RCA sectors, which amplifies regional comparative advantage of trade.

In the first and second rows of Table 10, we find that the mobility between occupations (B-O) increases rapidly, but mobility between regions (B-R) and mobility between occupation–region cells (B-O-R) are both smaller than in the baseline. Moreover, both interregional and international trade flows increase, and welfare improves the most out of all four cases. Ex ante, child all have equal talent in all occupations, meaning they can easily move to occupations different from those of their parents. As a result, more child flow to RCA occupations in their home region, hence the RCA sectors in each region can expand production without increasing their wage costs significantly. This is why the education reform generates the greatest increase in trade flows and the greatest aggregate welfare gains (3.78 times) in an open economy setting. Furthermore, high immigration costs still prevent young workers from moving across regions; relatively speaking, moving across occupations within regions is easier than moving across regions. Therefore, between-region and between-region–occupation immigration flows decrease.

Contrary to our expectations, the welfare inequality in Table **??** is even higher than at baseline because income inequality in China is mainly due to cross-regional income differences arising from the large productivity gaps across region–sector cells. Education reform magnifies regional comparative advantages by providing more skilled workers to each region's RCA sectors. This result is different from the predictions of closed economy models, in which an education reform that grants all children equal ex ante endowed skills substantially reduces income inequality, especially between-occupation income inequality.

In summary, we find that an education reforms is a promising policy for enhancing occupational mobility and aggregate welfare, but it fails to alleviate inequality because when the driving force behind income inequality is the productivity gap between regions, workers must move across regions, not only occupations, to generate true equality of opportunity.

4.3 Case 2: Trade Liberalization

We set the interregional trade costs to those of Canada. We choose Canada because Canada is a developed country with regional settings similar to those of China, but its trade costs are much lower. Tombe and Zhu (2019) estimate the trade costs in various Canadian sectors using the method of Tombe (2015). The average trade costs of the agricultural and nonagricultural sectors are 1.5 and 1.9, respectively.

The third row of Table 10, Case 2, presents results similar to those in Tombe and Zhu (2019), in that cross-regional and international trade and total welfare increase. In addition, we find that all types of labor mobility decline from their baseline levels because trade liberalization enables regions to become more specialized in production and trade; consequently, labor demand shifts toward the occupational skills used most intensively in the RCA sectors. In the steady state, the allocation of labor across occupations is more skewed toward occupations in RCA sectors within a region; hence, when children inherit this skewed skill distribution from their fathers, they are more likely to join their fathers' occupation, resulting in declines in cross-occupational mobility for the majority of children.

Children from families with an occupation in an RCA sector inherit their fathers' occupations and earn higher incomes than before trade liberalization. However, children from families with occupations in non-RCA sectors are worse off than at baseline because demand for their skills has shifted to other regions. Remember that immigration costs are still prohibitively high so that workers cannot move to pursue higher incomes. Therefore, Table 11 shows that under trade liberalization, the elasticity of intergenerational income increases, and Table ?? shows that the welfare gaps increase and that between-region and within-occupation differences are the main sources of these welfare gaps. These two forces result in welfare differences that are even stronger than at baseline. In summary, trade liberalization increases welfare at the expense of reduced intergenerational mobility across occupations and regions and greater inequality as measured by multiple indicators.

4.4 Case 3: Immigration Reform

We decrease cross-regional immigration costs by 39%, which is the estimated decrease that would occur if the household registration system were to disappear. Fan (2019) assigns China's household registration system a score of 0-6 to indicate its degree of openness. A score of 0 indicates complete closure, and 6 indicates complete openness. The author finds that each one-point increase in the hukou openness score corresponds to a migration cost reduction of 13% and a 20% increase in the number of migrants on average. The average score in 2000 was approximately 1. Tombe and Zhu (2019) Table ?? that the number of immigrants in 2005 increased by 44% from 2000, which means that China's openness score in 2005 was approximately 3. Therefore, interregional immigration costs would decrease by 3*13% if a score of 6 were reached, which would imply that the household registration system had been abolished. To be specific,

$$\mu_{ij,new}^{nm} = mu_{ij}^{nm} + (1 - mu_{ij}^{nm}) * 0.39, n \neq m$$

The fourth row of Table 10 reports that both the between-region and the between-region–occupation mobilities rise dramatically relative to the baseline when an immigration reform reduces immigration costs by 39%. However, cross-occupational mobility is slightly lower than at baseline. In the baseline model, conditional on moving across regions (BOR/BR), 65% of workers move to an occupation different from that of their father, while under the immigration reform, only 57% of cross-regional movers change their occupations, even though the absolute number of between-region–occupation moves is higher than at baseline. This means that workers with higher skill draws in all occupations are more likely to move to regions with more productive firms under lower immigration costs. Therefore, when immigration costs are sufficiently low, between-region–occupation moves may no longer be common in cross-regional mobility. In addition, the opportunity to move across regions but stay in the same occupation crowds out within-region cross-occupational mobility, which is why intergenerational occupational mobility is slightly lower under the immigration reform.

Looking more closely at the correlation between immigration and intergenerational occupational mobility, we find that there are two types of interregional movers. One type includes the children who inherited their parents' high skills for occupations that are frequent in their home region's RCA sectors. Such individuals are better off working in other regions where demand for their skills is higher than in their home region. The other type includes those children who have lucky draws for the occupational skills demanded by their home region's RCA sectors. When immigration costs are low enough, some individuals of this type with high enough skill draws move to other regions to work at more productive firms, which reinforces the positive sorting between workers and region–sector cells. Interregional mobility driven by the first type of mover increases intergenerational occupational mobility and income equality; that driven by the second type depresses intergenerational occupational mobility and may increase income inequality. In this counterfactual experiment, we find that immigration driven by the second type of move is greater than at baseline.

In Table ??, we find that when the immigration cost is reduced by 39%, the within-occupation welfare converges across regions. The total Theil index for welfare inequality falls significantly, and most welfare differences are due to between-region and between-occupation differences. Moreover, when children can move across regions, the correlation between the parents' income and the children's income is partially broken, and intergenerational income elasticity declines from baseline, as shown in Table 11. The total welfare gain under the immigration reform is higher than that under trade liberalization and lower than that under the education reform, but income inequality is the smallest out of all four cases.

4.5 Case 4: Combination of Trade Liberalization and Immigration Reform

We simultaneously decrease trade costs and immigration costs; the counterfactual results are reported in the last row of Table 10. We find that cross-regional mobility increases but that both cross-occupational and cross-regional–occupational mobility decrease slightly relative to their levels under trade liberalization in Case 2. The welfare gain is higher than under either the trade or immigration reform alone. In Table ??, we report that welfare inequality increases slightly relative to Case 3 because the between-region and between-occupation differences are larger than under the immigration reform alone, but the inequality measures are still much lower than in the other cases. In 11, the intergenerational income elasticity under the combined reform is the lowest out of all cases. Overall, we recommend that the interregional trade liberalization and immigration reforms be implemented at the same time, generating larger welfare gains without creating too much inequality.

Last, we want to address the issue of sensitivity in the calibration and counterfactual exercises. We find that changes in the immigration flow are sensitive to the absolute size and dispersion of T_{ij} across ij. The changes in trade flows and welfare are more responsive to the dispersion of productivities A_g^n across regions and sectors.

5 Conclusion

Since China's economic reform and opening to trade, different market-oriented reforms have been implemented. While the economy has been developing rapidly, the problems of income and opportunity inequality have become prominent. Our theoretical framework embeds the intergenerational occupational choice problem in a spatial trade model. We study the occupational and regional choices of children under the intergenerational transmission of occupational skill and intergenerational regional–occupational mobility costs and the impact of an education reform, trade liberalization and an immigration reform on intergenerational regional–occupational mobility, welfare and inequality.

In the model, there are two factors that inhibit intergenerational occupational and income mobility. First, intergenerational correlations across human capital endowments cause the children of higher-income parents to be more skilled in high-income occupations. Second, when the majority of cross-regional movers are those who draw drastically different talents from the skill distribution inherited from their parents, young movers also change to an occupation different from that of their parents when immigrating to other regions; therefore, an immigration reform can potentially promote occupational mobility in addition to regional mobility.

We run four counterfactual experiments after calibrating the model: Case 1, an education reform that gives all children the same ex ante distribution of endowed skills; Case 2, a trade liberalization scheme that reduces all cross-regional trade costs to their level in Canada; Case 3, an immigration reform that eliminates the hukou system and decreases immigration costs by 39%; and Case 4, a combination of Case 2 and Case 3. We then quantitatively compare the outcomes in terms of immigration flows across regions and occupations, trade flows, welfare gains, and inequality. We ask the following questions: Which reform most effectively promotes intergenerational occupational mobility? Are immigration barriers also a wall to occupational mobility? Which reforms should be adopted to generate the largest welfare gains? Which reform should be chosen to eliminate inequality?

We obtain the following policy-relevant results from our quantitative counterfactual experiments. First, the education reform generates the highest level of intergenerational occupational mobility and the greatest welfare gain by transferring more workers from all family backgrounds into the RCA sectors of their home regions without significantly increasing wages; however, the education reform cannot reduce inequality because the primary source of inequality in China is cross-regional productivity gaps. Second, trade liberalization increases welfare at the expense of regional and occupational mobility and increases inequality by strengthening regional specialization and the concentration of labor demand on those occupational skills required by the RCA sectors. Third, the interregional immigration reform creates the largest cross-regional immigration flows and lowest inequality; however, intergenerational occupational mobility is actually slightly lower than at baseline because low immigration costs also allow more workers to stay in the same occupation as their parents when moving to other regions, as such workers may move only in order to be matched with more productive firms. Therefore, immigration barriers are not necessarily correlated with occupational mobility. Last, the combined trade liberalization and immigration reform strikes a balance between large welfare gains and low inequality.

In summary, we suggest that policy makers simultaneously reduce immigration costs when opening up regional trade, as that combined reform generates the greatest social mobility and good welfare gains. In contrast, the education reform that eliminates ex ante skill differences across parental occupations generates the greatest welfare gains by magnifying regional RCAs but cannot beat the immigration reform in terms of social equality because the education reform helps workers move across occupations within their home region only, while cross-regional income differences due to productivity gaps still persist when immigration costs are prohibitive.

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6 Appendix

6.1 Model Solution

Given that the father works in occupation i and lives in region n and his child chooses occupation j and region m, the individual optimization problem is as follows:

$$\max_{\left(c_{ij}^{nm}(g), s_{ij}^{nm}, e_{ij}^{nm}\right)} U_{ij}^{nm}(\epsilon_i j) = (1 - \sum_{g \in \mathbb{G}} \alpha_g) log \left(1 - s_{ij}^{nm}\right) + \sum_{g \in G} \alpha_g log c_{ij}^{nm}(g),$$

$$s.t. \sum_{g \in \mathbb{G}} p_g^m c_{ij}^{nm}(g) = \mu_{ij}^{nm} w_j^m \epsilon_{ij} h_{ij}^{nm},$$

$$h_{ij}^{nm} = \left(s_{ij}^{nm}\right)^{\varphi_j} \left(e_{ij}^{nm}\right)^{\eta}.$$

Solving the above optimization problem, we obtain eq. (8), eq. (7) and eq. (9). We substitute eq. (8) into the net income and budget constraint eq. (5), and we derive the expression for net income and the consumption of consumer goods as follows:

$$\mu_{ij}^{nm} I_{ij}^{nm}(\epsilon_{ij}) = \left(\eta^{\eta} \mu_{ij}^{nm} w_j^m \epsilon_{ij} s_j^{\varphi_j}\right)^{\frac{1}{1-\eta}}, \tag{47}$$

and

$$c_{ij,g}^{nm} = \frac{\alpha_g}{p_g^m \left(\sum_{g \in \mathbb{G}} \alpha_g\right)} (1 - \eta) \mu_{ij}^{nm} I_{ij}^{nm}(\epsilon_{ij}). \tag{48}$$

Now, we elaborate on the calculation of eq. (14). To simplify the calculation, we denote

$$\omega_{ij}^{nm} = \mu_{ij}^{nm} V_j^m \left(1 - s_j\right)^B$$

and

$$(U_{ij}^{nm}(\epsilon_j))^* \propto \omega_{ij}^{nm} \epsilon_{ij}.$$

$$
\begin{aligned}
p_{ij}^{nm} &= Pr\left((U_{ij}^{nm}(\epsilon_{ij}))^* \geq \max_{\forall s \neq m, \forall k \neq j} (U_{ik}^{ns}(\epsilon_{ik}))^* \right) \\
&= Pr\left(\left(U_{ij}^{nm}\right)^* (\epsilon_{ij}) \geq U \mid \max_{\forall s \neq m, \forall k \neq j} (U_{ik}^{ns}(\epsilon_{ik}))^* < U \right), \exists U \\
&= Pr\left(\epsilon_j \geq \frac{U}{\omega_{ij}^{nm}} \mid \max_{\forall s \neq m, \forall k \neq j} \epsilon_{ik} < \frac{U}{\omega_{ik}^{ns}} \right) \\
&= \int 1 - e^{-T_{ij}\left(\frac{U}{\omega_{ij}^{nm}}\right)^{-\theta}} de^{-\sum_{s\neq m}\sum_{k\neq j} T_{ik}\left(\frac{U}{\omega_{ik}^{ns}}\right)^{-\theta}} \\
&= \frac{T_{ij}\left(\omega_{ij}^{nm}\right)^{\theta}}{\sum_{s\in\mathbb{N}}\sum_{k\in\mathbb{O}} T_{ik}\left(\omega_{ik}^{ns}\right)^{\theta}} \\
&= \frac{\left(\vartheta_{ij}^{nm}\right)^{\theta}}{\sum_{s\in\mathbb{N}}\sum_{k\in\mathbb{O}}\left(\vartheta_{ik}^{ns}\right)^{\theta}},
\end{aligned}
$$

where $\vartheta_{ij}^{nm} = T_{ij}^{\frac{1}{\theta}} \omega_{ij}^{nm}$.

Then, we calculate the distribution of personal skill endowments in the job market for occupation j in region m. Given that the parent works in occupation i in region n and the child chooses occupation j in region m, the distribution of child skills ϵ_{ij}^{nm} determines the distribution of human capital endowments by region and occupation. The child skill distribution is as follows:

$$
\left(U_{ij}^{nm}(\epsilon_{ij}^{nm})\right)^* \equiv \max_{s,k} (U_{ik}^{ns})^* = \max_{s,k} (\epsilon_{ik}^{ns}\omega_{ik}^{ns}), \forall s \in \mathbb{N}, \forall k \in \mathbb{O},
$$

$$
\begin{aligned}
Pr\left(\left(U_{ij}^{nm}(\epsilon_{ij}^{nm})\right)^* < y \right) &= Pr\left(\epsilon_{ik}^{ns} < \frac{y}{\omega_{ik}^{ns}} \right), \forall s \in \mathbb{N}, \forall s \in \mathbb{N}, k \in \mathbb{O} \\
&= e^{\left(-\sum_{s\in\mathbb{N}}\sum_{k\in\mathbb{O}} T_{i,k}\left(\frac{y}{\omega_{ik}^{ns}}\right)^{-\theta}\right)}.
\end{aligned}
$$

Furthermore, the distribution of ϵ_{ij}^{nm} is:

$$
\begin{aligned}
G_{\epsilon_{ij}^{nm}}(x) &= Pr\left(\epsilon_{ij}^{nm} < x\right) \\
&= Pr\left(\omega_{ij}^{nm}\epsilon_{ij}^{nm} < \omega_{ij}^{nm} x\right) \\
&= Pr\left(\left(U_{ij}^{nm}(\epsilon_{ij}^{nm})\right)^* < \omega_{ij}^{nm} x\right) \\
&= e^{\left(-\sum_{s\in\mathbb{N}}\sum_{k\in\mathbb{O}} T_{ik}\left(\frac{\omega_{ik}^{ns}}{\omega_{ij}^{nm}}\right)^{\theta} x^{-\theta}\right)} \\
&= e^{\left(\frac{-T_{ij}x^{-\theta}}{p_{ij}^{nm}}\right)}
\end{aligned}
$$

Both $E\left(\epsilon_{ij}^{nm}\right)^q$ are used when calculating total human capital and income by region–occupation.

$$
\begin{aligned}
E\left(\epsilon_{ij}^{nm}\right)^{q} &= \int_{0}^{\infty}\left(\epsilon_{ij}^{nm}\right)^{q} dG\left(\epsilon\right) \\
&= \left(\frac{T_{ij}}{p_{ij}^{nm}}\right)^{\frac{q}{\theta}} \Gamma\left(1-\frac{q}{\theta}\right), \forall q > 0
\end{aligned}
\tag{49}
$$

Given the father's region and occupation (n,i) and the child's choice of region–occupation (m,j), the average human capital of immigrants to region m is $APH_{ij}^{nm} = \left[h_{ij}^{nm} E\epsilon_{ij}^{nm}\right]$. Substituting this into eq. (49), we can obtain:

$$
\begin{aligned}
APH_{ij}^{nm} &= h_{ij}^{nm} E(\epsilon_{ij}^{nm}) \\
&= \left(\eta^{\eta} s_j^{\varphi_j}\right)^{\frac{1}{1-\eta}} \left(\mu_{ij}^{nm} w_j^m\right)^{\frac{\eta}{1-\eta}} E\left(\epsilon_{ij}^{nm}\right)^{\frac{1}{1-\eta}} \\
&= \left(\eta^{\eta} s_j^{\varphi_j}\right)^{\frac{1}{1-\eta}} \left(\mu_{ij}^{nm} w_j^m\right)^{\frac{\eta}{1-\eta}} \left(\frac{T_{ij}}{p_{ij}^{nm}}\right)^{\frac{1}{\theta(1-\eta)}} \Gamma\left(1-\frac{1}{\theta\left(1-\eta\right)}\right) \\
&= \left(\frac{\mu_{ij}^{nm} w_j^m}{\prod_{g\in\mathbb{G}}\left(p_{\alpha_g}^m\right)^{\frac{\alpha_g}{\sum_{g\in\mathbb{G}}\alpha_g}}}\right)^{-1} \left(1-s_j\right)^{-\frac{B}{1-\eta}} \left(\sum_{s\in\mathbb{N}}\sum_{k\in\mathbb{O}}\left(\vartheta_{ik}^{ns}\right)^{\theta}\right)^{\frac{1}{\theta(1-\eta)}} \Gamma\left(1-\frac{1}{\theta\left(1-\eta\right)}\right).
\end{aligned}
$$

When the father is in occupation i in region n, the average net income of child in occupation j in region m is

$$
\begin{aligned}
NI_{ij}^{nm} &= \mu_{ij}^{nm} E\left[I_{ij}^{nm}(\epsilon_{ij}^{nm})\right] \\
&= \mu_{ij}^{nm} w_j^m APH_{ij}^{nm} \\
&= \left(\eta^{\eta}\mu_{ij}^{nm} w_j^m s_j^{\varphi_j}\right)^{\frac{1}{1-\eta}} \left(\frac{T_{ij}}{p_{ij}^{nm}}\right)^{\frac{1}{\theta(1-\eta)}} \Gamma\left(1-\frac{1}{\theta\left(1-\eta\right)}\right) \\
&= \prod_{g\in\mathbb{G}}\left(p_g^m\right)^{\frac{\alpha_g}{\sum_{g\in\mathbb{G}}\alpha_g}} \left(1-s_j\right)^{-\frac{B}{1-\eta}} \left(\sum_{s\in\mathbb{N}}\sum_{k\in\mathbb{O}}\left(\vartheta_{ik}^{ns}\right)^{\theta}\right)^{\frac{1}{\theta(1-\eta)}} \Gamma\left(1-\frac{1}{\theta\left(1-\eta\right)}\right).
\end{aligned}
$$

Based on eq. (48), the total consumption of good g is the sum of the individual consumption of all workers in all occupations in region m in eq. (9). Let c_g^m be the consumption of good g in region m.

$$
\begin{aligned}
c_g^m &= \sum_{n\in\mathbb{N}}\sum_{j\in\mathbb{O}}\sum_{i\in\mathbb{O}} \pi_i^n p_{ij}^{nm} E\left[c_{ij}^{nm,g}(\epsilon_{ij}^{nm})\right] \\
&= \sum_{n\in\mathbb{N}}\sum_{j\in\mathbb{O}}\sum_{i\in\mathbb{O}} f_i^n p_{ij}^{nm} \frac{\alpha_g}{p_g^m\left(\sum_{g\in\mathbb{G}}\alpha_g\right)}\left(1-\eta\right)\mu_{ij}^{nm} I_{ij}^{nm} \\
&= \frac{\alpha_g\left(1-\eta\right)}{p_g^m\sum_{g\in\mathbb{G}}\alpha_g}\sum_{n\in\mathbb{N}}\sum_{j\in\mathbb{O}}\sum_{i\in\mathbb{O}} f_i^n\left(p_{ij}^{nm}\right)\left(\eta^\eta\mu_{ij}^{nm}w_j^m s_j^{\varphi_j}\right)^{\frac{1}{1-\eta}}\left(\frac{T_{ij}}{p_{ij}^{nm}}\right)^{\frac{1}{\theta(1-\eta)}}\Gamma\left(1-\frac{1}{\theta\left(1-\eta\right)}\right).
\end{aligned}
\tag{50}
$$

The total welfare in region m is given by $W^m \propto \sum_{n\in\mathbb{N}}\sum_{i\in\mathbb{O}}\sum_{j\in\mathbb{O}} E\left(U_{ij}^{nm}\right)^*$. Substituting eq. (11) into the above equation, we can obtain:

$$
W^m = \sum_{n\in\mathbb{N}}\sum_{i\in\mathbb{O}}\sum_{j\in\mathbb{O}} f_i^n\left(p_{ij}^{nm}\right)^{\left(1-\frac{1}{\theta}\right)}\left(T_{ij}\right)^{\frac{1}{\theta}}\mu_{ij}^{nm}V_j^m\left(1-s_j\right)^B\Gamma\left(1-\frac{1}{\theta}\right)
$$

Furthermore, total domestic welfare is $W = \sum_{m\in\mathbb{N}} W^m$.

Table 1: Calibrated Model Parameters and Initial Values

α_1	0.0418	Good 1's preference weight
α_2	0.0012	Good 2's preference weight
α_3	0.0763	Good 3's preference weight
α_4	0.0353	Good 4's preference weight
α_5	0.0082	Good 5's preference weight
α_6	0.0022	Good 6's preference weight
α_7	0.0336	Good 7's preference weight
α_8	0.2116	Good 8's preference weight
η	0.103	Share of human capital output spent on education
κ	4	Elasticity of trade
θ	2	Elasticity of migrate
f_j^n	Data	Shares of the father population in region–occupation (n,j)
π_g^{nm}	Data	Bilateral trade shares
p_{ij}^{nm}	Data	Bilateral migration shares

Note: This table displays the model parameters and targeted moments and provides a description of each.

Table 2: γ_{jg}

Sector	Occupation	γ_{jg}	Sector	Occupation	γ_{jg}
Agriculture	Principals	0.004	Ele-Gas-Water	Principals	0.056
Agriculture	Pro-techs	0.028	Ele-Gas-Water	Pro-techs	0.179
Agriculture	Clerks	0.004	Ele-Gas-Water	Clerks	0.147
Agriculture	Com-services personnel	0.003	Ele-Gas-Water	Com-services personnel	0.12
Agriculture	Farmers	0.956	Ele-Gas-Water	Farmers	0.012
Agriculture	Manu-trans operatios	0.005	Ele-Gas-Water	Manu-trans operators	0.486
Mining	Principals	0.0720	Construction	Principals	0.055
Mining	Pro-techs	0.102	Construction	Pro-techs	0.102
Mining	Clerks	0.066	Construction	Clerks	0.040
Mining	Com-services personnel	0.051	Construction	Com-services personnel	0.031
Mining	Farmers	0.004	Construction	Farmers	0.005
Mining	Manu-trans operators	0.705	Construction	Manu-trans operators	0.768
Light-ind	Principals	0.067	Retail-Trans	Principals	0.072
Light-ind	Pro-techs	0.049	Retail-Trans	Pro-techs	0.055
Light-ind	Clerks	0.048	Retail-Trans	Clerks	0.050
Light-ind	Com-services personnel	0.081	Retail-Trans	Com-services personnel	0.578
Light-ind	Farmers	0.013	Retail-Trans	Farmers	0.005
Light-ind	Manu-trans operators	0.743	Retail-Trans	Manu-trans operators	0.239
Heavy-ind	Principals	0.083	Other Services	Principals	0.084
Heavy-ind	Pro-techs	0.117	Other Services	Pro-techs	0.394
Heavy-ind	Clerks	0.076	Other Services	Clerks	0.220
Heavy-ind	Com-services personnel	0.089	Other Services	Com-services personnel	0.230
Heavy-ind	Farmers	0.002	Other Services	Farmers	0.005
Heavy-ind	Manu-trans operators	0.633	Other Services	Manu-trans operators	0.067

Note: γ_{jg} is the share of wages earned by workers in occupation j in sector g.

Table 3: T_{ij}

	Child's Occupation					
Father's Occupation	Principals	Clerks	Pro-techs	Manu-trans	Com-services	Farmers
Principals	0.641	0.225	0.080	0.062	0.148	0.061
Clerk	0.025	0.043	0.017	0.022	0.029	0.011
Pro-techs	0.011	0.025	0.010	0.024	0.016	0.008
Manu-trans	0.002	0.014	0.014	0.020	0.017	0.014
Com-service	0.017	0.028	0.441	0.022	0.066	0.012
Farmers	0.000	0.001	0.001	0.003	0.004	0.060

Note: The occupations in this table are sorted according to the average occupational income in 2005 in descending order.

Table 4: μ^{nm}

	Child's Region							
Father's Region	Northeast	Jingjin	North coast	East coast	South coast	Central	Northwest	Southwest
Northeast	0.688	0.179	0.103	0.433	0.041	0.030	0.055	0.030
Jingjin	0.030	0.803	0.029	0.058	0.000	0.048	0.000	0.012
North coast	0.056	0.098	0.572	0.268	0.022	0.051	0.033	0.009
East coast	0.048	0.071	0.066	0.943	0.054	0.067	0.048	0.057
South coast	0.023	0.032	0.022	0.547	0.766	0.065	0.022	0.031
Central	0.038	0.064	0.040	0.140	0.138	0.530	0.112	0.069
Northwest	0.187	0.054	0.027	0.272	0.055	0.076	0.768	0.012
Southwest	0.156	0.154	0.019	0.098	0.104	0.273	0.199	0.821

Note: $\mu_{nm} = \sum_{i\in\mathbb{O}}\sum_{j\in\mathbb{O}} f_i^n p_{ij}^{nm} \mu_{ij}^{nm}$.

Table 5: μ_{ij}

	Child's Occupation					
Father's Occupation	Principals	Clerks	Pro-techs	Manu-trans	Com-services	Farmers
Principals	0.139	0.552	0.722	0.913	0.964	0.548
Clerk	0.369	0.504	0.747	0.879	0.985	0.659
Pro-techs	0.309	0.510	0.727	0.724	0.954	0.596
Manu-trans	0.490	0.680	0.479	0.834	0.974	0.632
Com-service	0.282	0.348	0.043	0.728	0.959	0.635
Farmers	0.392	0.555	0.556	0.729	0.924	0.456

Note: $\mu_{ij} = \sum_{n\in\mathbb{N}}\sum_{m\in\mathbb{N}} f_i^n p_{ij}^{nm} \mu_{ij}^{nm}$

Table 6: Average Cross-Regional Trade Costs

	Exporter								
Importer	Northeast	Jingjin	North coast	East coast	South coast	Central	Northwest	Southwest	ROW
Northeast		2.202	2.1	2.562	2.666	2.34	2.712	2.507	6.6
Jingjin	2.969		1.783	2.96	3.43	2.917	3.627	4.394	4.984
North Coast	3.875	1.688		2.666	3.316	2.487	4.45	5.767	7.288
East coast	3.697	2.752	2.626		2.784	2.173	3.364	3.893	4.817
South coast	2.354	2.261	1.959	1.477		1.604	2.461	1.627	3.751
Central	2.874	2.649	2.038	1.776	2.424		2.703	2.748	7.941
Northwest	2.174	1.817	1.607	1.804	2.038	1.723		1.737	5.873
Southwest	3.024	3.142	2.735	2.577	2.136	2.6	2.731		8.58
ROW	15.967	32.994	24.471	22.257	12.022	35.74	38.308	25.723	

Note:$\tau^{nm} = \frac{\sum_g \tau_g^{nm} X_g^{nm}}{\sum_g X_g^{nm}}$.

Table 7: Average Trade Costs by Sector

Agri	Mining	Light-Ind	Heavy-Ind	Ele-Gas-Water	Cons	Retail-Trans	Other Services
5.520	3.710	3.184	11.663	7.014	10.836	20.283	10.853

Note: $\tau_g = \frac{\sum_n \sum_m \tau_g^{nm} X_g^{nm}}{\sum_n \sum_m X_g^{nm}}$.

Table 8: Intergenerational Occupational Mobility

	Child's Occupation					
Father's Occupation	Principals	Clerks	Pro-techs	Operators	Com-services	Farmers
Principals	0.127	0.135	0.200	0.223	0.209	0.107
Clerks	0.020	0.258	0.197	0.246	0.220	0.060
Pro-techs	0.013	0.079	0.514	0.167	0.122	0.104
Manu-trans	0.007	0.053	0.081	0.526	0.213	0.120
Com-services	0.009	0.063	0.096	0.285	0.446	0.101
Farmers	0.003	0.012	0.022	0.223	0.084	0.655

Note: 1.$p_{ij} = \sum_n \sum_m p_{ij}^{nm}/N^2$; 2. The occupations in this article are sorted according to the average occupational income in 2005 in descending order.

Table 9: Intergenerational Regional Mobility

	Child's Area							
Father's Area	Northeast	Jingjin	North coast	East coast	South coast	Central	Northwest	Southwest
Northeast	0.963	0.020	0.007	0.003	0.004	0.000	0.002	0.001
Jingjin	0.000	0.997	0.001	0.001	0.000	0.001	0.000	0.000
North coast	0.001	0.023	0.971	0.003	0.000	0.001	0.000	0.000
East coast	0.001	0.003	0.001	0.988	0.003	0.003	0.001	0.001
South coast	0.000	0.001	0.000	0.002	0.993	0.002	0.000	0.001
Central	0.001	0.009	0.002	0.032	0.037	0.913	0.002	0.004
Northwest	0.003	0.006	0.002	0.003	0.005	0.004	0.977	0.000
Southwest	0.000	0.006	0.001	0.015	0.027	0.002	0.002	0.949

Note: $p_{nm} = \sum_i \sum_j p_{ij}^{nm}/O^2$.

Table 10: Counterfactual Experiment Results—Intergenerational Regional–Occupational Mobility and Trade Flow Changes

	Share of young workers who migrate			Δ Trade		Δ Welfare
	B-O-R	B-O	B-R	Internal	External	
Baseline	0.013	0.334	0.030	0.000	0.000	0.000
Education	0.015	0.452	0.019	16.173	136.398	8.235
Trade	0.016	0.320	0.030	4.074	6.742	1.614
Immigration	0.253	0.308	0.579	12.192	16.283	3.471
Trade and Immigration	0.277	0.336	0.639	9.732	13.738	2.891

Note: 1. Case 1 imposes an equal intergenerational transmission of endowed skills across occupations. Case 2 reduces trade costs to the Canadian level. Case 3 reduces immigration costs by 39%. Case 4 combines Case 2 and Case 3. 2. B-O-R is the number of child who move across region–occupation cells. B-O is the number of child who move across occupations. B-R is the number of child who migrate across regions. 3. $\Delta trade = \frac{\Delta \sum_m \; sum_g \pi_g^{nm} X_g^m}{\sum_m \sum_g \pi_g^{nm} X_g^m}$; $\Delta Welfare = \frac{\Delta W}{W}$.

Table 11: Counterfactual Analysis Results—Intergenerational Income Elasticity

Scenario	Intergenerational Income Elasticity
Baseline	0.32
Education	0.84
Trade	0.35
Immigration	0.29
Trade and Immigration	0.27

Note: Case 1 imposes an equal intergenerational transmission of endowed skills across occupations. Case 2 reduces trade costs to the Canadian level. Case 3 reduces immigration costs by 39%. Case 4 combines Case 2 and Case 3.

Table 12: Counterfactual Experiment Results—Theil Index for W_i^n

W_i^n	Total	B-R ratio	W-R ratio	B-O ratio	W-O ratio
Baseline	1.19	49.59	50.41	30.51	69.49
Education	1.95	61.22	38.78	57.50	42.50
Trade	1.22	51.28	48.72	29.66	70.34
Immigration	0.91	79.59	20.41	81.34	18.66
Trade and Immigration	1.11	78.63	21.37	83.31	16.70

Note: 1. Case 1 imposes an equal intergenerational transmission of endowed skills across occupations. Case 2 reduces trade costs to the Canadian level. Case 3 reduces immigration costs by 39%. Case 4 combines Case 2 and Case 3. 2. The B-O ratio is the share of the Theil index that is due to between-occupation inequality, the W-O ratio is the share of the Theil index that is due to within-occupation inequality, the B-R ratio is the share of the Theil index that is due to between-region inequality, and the W-R ratio is the share of the Theil index that is due to within-region inequality.

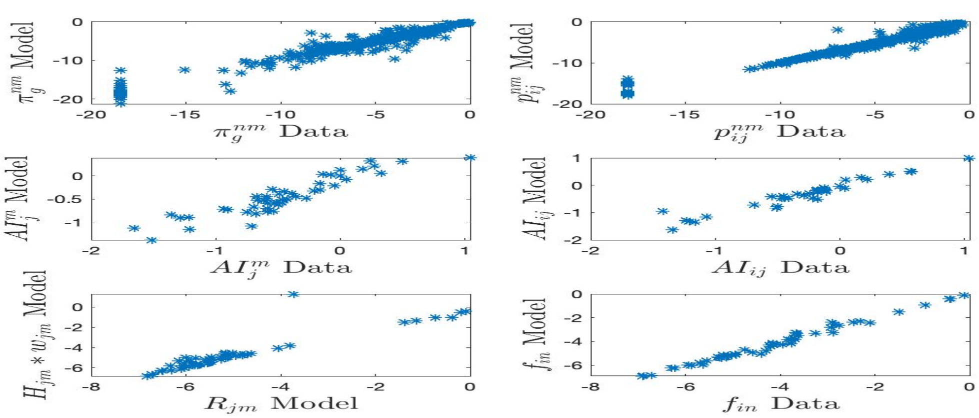

Figure 1: Data- and Model-Implied Values of π_g^{nm}, p_{ij}^{nm},AI$_j^m$, AI_{ij}, R_j^m and f_i^n