Physical and Human Capital Accumulation in a Spatial Economy

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Abstract

We study how spatial factor accumulations respond to economic shocks and their implications for quantifying aggregate and distributional impacts. To examine their responses and implications, we develop a dynamic spatial model that incorporates capital accumulation and skill acquisition. Focusing on China's trade liberalization and infrastructure expansion in the early 2000s, we show that allowing for capital accumulation amplifies welfare gains and intensifies inequality across skill types, while skill acquisition attenuates impacts on skill premiums by balancing skill supply in response to shocks. Our findings also highlight the critical role of capital-skill interactions in shaping aggregate and spatial impacts, suggesting that both capital and skill adjustments are essential to understanding the full impacts of economic shocks on welfare and inequality.

Keywords: international trade; skill premium; economic geography; capital accumulation

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1 Introduction

A central question in spatial economics is how economic shocks propagate within a country. In the short run, the answers depend on geography, industrial composition, and factor mobility. In the long run, factor accumulations such as physical and human capital adjustment might play increasingly important roles. For example, a trade liberalization shock can reduce the cost of sourcing investment goods and hence increase the rate of capital accumulation, magnifying the welfare impact of the trade shock[1]. The same shock might encourage or discourage human capital accumulation, depending on whether the country has a comparative advantage in the skilled or unskilled sectors. Moreover, factor accumulations interact with each other: faster physical capital accumulation could affect the return to skill, leading to faster human capital accumulation and vice versa. Understanding the rich dynamics of both physical and human capital accumulation and how they respond to and propagate economic shocks is a question that requires careful modeling of both forces in general equilibrium. Such a framework is currently lacking in the literature.

We develop a dynamic spatial model with endogenous physical and human capital accumulation to study spatial factor accumulation and its roles on determining the aggregate and distributional impacts of economic shocks. In particular, we incorporate heterogeneous workers and endogenous skill acquisition into a dynamic spatial framework with forward-looking migration and capital accumulation decisions (Caliendo et al., 2019; Kleinman et al., 2023). In the model, workers are born unskilled and can choose to become students and, subsequently, skilled workers for the rest of their lifetimes. Acquiring skills incurs two costs: a fixed cost that captures the financial and psychological costs of skill acquisition and an opportunity cost of foregone income during one's spell as a student. Upgrading skills brings in higher income and lowers migration costs, as low-skilled workers might face discrimination in destination locations due to policy barriers. On the supply side, we introduce capital-skill complementarity to anchor the interaction between physical and human capital accumulations in the long run. The accumulation of capital stock in each location is determined by the forward-looking investment decision of the landlord as in Kleinman et al. (2023). Each

[1] For instance, see Ravikumar et al. (2019) and Artuc et al. (2022) for discussions on how trade impacts depend on capital accumulation.

location's skill composition is determined by the inflow of skilled and unskilled workers as well as the skill upgrading decisions made by local unskilled workers.

The model highlights the critical roles played by the interaction of physical and human capital accumulation in propagating economic shocks across space. Consider a hypothetical productivity shock that uniformly increases the local productivity of all locations in a country. The productivity boom reduces investment costs and promotes physical capital accumulation. More capital stocks boost production and welfare. Thus, allowing investment amplifies the total welfare gain compared to a traditional spatial model without capital accumulation. In addition, as the capital accumulation rate increases, the marginal return of skilled workers is relatively greater than that of unskilled workers, magnifying the skill premium increase driven by the productivity shock. While skill acquisition only limitedly affects welfare change in the absence of capital accumulation, it strongly enlarges welfare gain when capital accumulation presents, suggesting an interaction effect between physical and human capital accumulation. Since endogenous skill acquisition allows skill supply adjustment in response to the shock, it attenuates the shock-induced skill premium increase. In the above example, incorporating factor accumulation has rich implications for quantitative analysis. How does endogenous factor accumulation affect the impacts of other shocks, such as trade liberalization and infrastructure improvement? How does it change the shock's spatial impacts, such as shock-driven migration, the spatial distribution of the local impacts, and winners and losers in space? We aim to provide answers to these questions.

We quantify our model in the context of China, a country that experienced drastic trade liberalization and massive infrastructure investment in the past two decades. We model four sectors that differ in trade costs and factor intensity and map the geographical units to "prefectures" in China. We utilize various datasets to invert the model to recover locational fundamentals and structurally estimate the skill upgrading and type-specific migration costs along the transition path. Migration costs consist of geographic travel costs and type-specific policy barriers. Consistent with previous literature, policy barriers in China for skilled and unskilled workers are significant, equivalent to 2.2 and 2.5 times respectively the geographic travel costs between an average city-pair within China, with unskilled workers facing higher policy barriers. The skill upgrading costs are also considerable, equivalent to 74 percent of an unskilled worker's lifetime utility.

To highlight the roles of factor accumulation in explaining the aggregate and spatial impacts of economic shocks, we focus on three key questions: 1) In the absence of skill acquisition, does an economic shock impact the economy equally with and without endogenous capital accumulation? 2) In the absence of physical capital accumulation, does the same shock impact the economy similarly with and without skill upgrading? and 3) Conditional on capital accumulation, does adding skill upgrading affect the quantitative impacts of the shock? To answer these questions, we consider four model setups: the benchmark model with physical and human capital accumulation, the model with skill acquisition but no capital accumulation, the model with endogenous capital accumulation but no upskilling, and the bare-bone model without both factor accumulation. We compare the baseline economy for each model setup that captures factual economic shock to a counterfactual economy without the shock. We measure the impacts of a shock on capital stocks, skill ratio, welfare, and skill premium and explore how the impacts change across different model setups.

In quantitative analysis, we focus on two historical shocks happening in early 2000s China: China's accession to the WTO in 2001 and its large-scale investment in domestic infrastructure during 2000-2015. Back in the early 2000s, as an unskill-abundant country relative to the ROW, China had a comparative advantage in the unskilled sector. Thus, in a conventional quantitative trade model, trade liberalization favors unskilled workers in China due to the Stoper-Samuelson theorem. In the counterfactual experiment using the bare-bone model, we find a similar result that the average unskilled real wage increases by 2.4 percent, but the skilled real wage only increases by 0.7 percent in steady states. Endogenizing factor accumulations significantly amplifies welfare gain, particularly for skilled workers: the impacts on unskilled and skilled real wages become 3.6 and 3.3 percent, respectively. Such amplification effect is mainly due to accelerated capital formation fueled by lower investment costs following trade liberalization. Ignoring capital adjustment will shut down this channel and underestimate the welfare impact of trade.

More interestingly, We find that capital accumulation and skill acquisition interact with each other in response to the trade shock: endogenous capital accumulation alleviates the trade-driven skill downgrading, and allowing skill adjustment weakens the trade-induced capital growth. This interaction response between factor accumulations is mainly due to capital-skill complementarity: the faster capital accumulation due to trade liberalization increases the marginal return on skill and thus alleviates skill downgrading.

Regarding spatial impacts of trade, factor accumulations impose strong heterogeneous spatial impacts and substantially differentiate the winners and losers within China generated by the trade shock. Due to the coastal cities' geographic closeness to the ROW, they reap the most gains from trade liberalization. They attract more migrants, produce more, and provide higher real wages than inland cities. Allowing capital and skill adjustment reinforces their locational advantages: the unskilled and skilled real wage impact gaps between the top winner and the last winner widen by 3 and 5 times, respectively. And the trade shock drives a larger spatial disparity in the local workforce changes. For example, one of the top coastal winners, Dalian, is 7 times more effective in attracting migrants than it would be if there were no factor accumulation, while one of the inland losers, Chengdu, loses 5 times more workers [2].

Factor accumulation plays a similar role in explaining the impacts of infrastructure improvement. It magnifies welfare gains and enlarges the spatial heterogeneity in local impacts. Moreover, it changes the shock's nature in affecting the inequality between skilled workers and unskilled workers. The shock is close to skill-neutral in the bare-bone model simulation, as it only slightly increases skill premium by 0.4 percent. However, it becomes strongly skill-biased conditional on capital formation: infrastructure improvement raises skill premium by 1.4 percent, as the shock drives capital growth which increases the return of skill. The shock becomes slightly unskill-biased under the simulation with skill acquisition but no capital accumulation: skill premium reduces by 0.2 percent because of the shock-induced larger supply of skill. Finally, incorporating both keeps the shock skill-biased as skill premium increases by 1.3 percent — the positive force from capital accumulation dominates the negative one of upskilling.

This paper mainly speaks to the literature on quantitative spatial models (Allen and Arkolakis, 2014; Ahlfeldt et al., 2015; Caliendo et al., 2019; Allen and Arkolakis, 2022;

[2] More specifically, in the bare-bone model simulation and the benchmark model simulation, the impacts of the local population in Dalian are 1.3 and 9.9 percent increase respectively, while these in Chengdu are -1.1 to -5.1 percent respectively.

Kleinman et al., 2023). The closest to this paper is Kleinman et al. (2023), relative to which we introduce endogenous skill acquisition and show rich interactions between factor accumulations across space. Our model is well-suited for studying skill premiums, as it incorporates multiple sectors, multiple production factors, and capital-skill complementarity into this strand of models.

It is also related to a broad literature investigating the spatial impact of trade (Feenstra and Hanson, 1996; Goldberg and Pavcnik, 2007; Helpman et al., 2010; Parro, 2013; Autor et al., 2013, 2021), infrastructure investment (Faber, 2014; Donaldson and Hornbeck, 2016; Banerjee et al., 2020), and other economic shocks such as internal migration liberalization (Bryan and Morten, 2019). Many papers in this literature assume fixed endowments of production factors and abstract away from the spatial and intertemporal dimensions. A strand of papers particularly related to our research is the trade models that endogenize factor endowments at the aggregate level, such as Findlay and Kierzkowski (1983), Borsook (1987), Falvey et al. (2010), and Blanchard and Willmann (2016). Our paper introduces the space and time dimension to this literature. We show that factor endowments respond to economic shocks differently across space within a country, and their response to shocks is conditional on other factors' response.

Finally, we also contribute to the literature studying China's spatial economy (Fan, 2019; Tombe and Zhu, 2019; Ma and Tang, 2020, 2024; Cai et al., 2022). Our work is closest to Fan (2019), which considers the spatial impacts of shocks in a static model with exogenously determined capital stock and skill types. Relative to Fan (2019), we endogenize capital accumulation and skill acquisition in a dynamic framework. Our results show that the endogenous response of factor accumulation could lead to drastically different quantification results of economic shocks.

The rest of the paper is structured as follows. Section 2 describes our dynamic spatial framework; Section 3 takes our model to China's economy and shows how to calibrate the model; Section 4 discusses our quantitative results, and Section 5 concludes.

2 Model

2.1 The Environment

The model endogenizes skill formation and incorporates capital-skill complementarity into a general equilibrium dynamic spatial similar to Kleinman et al. (2023). The economy has N geographically segmented locations indexed by i and J sectors indexed by j. Time is discrete and indexed by $t = 0, 1, 2, \cdots, \infty$. Two types of agents, workers and landlords, reside in each location.

2.2 Workers

There are three types of workers: unskilled workers, skilled workers, and students. Unskilled and skilled workers are full time workers. They inelastically supply one unit of type-specific labor each period and earn income accordingly. Students are part-time workers and only provide a fraction of unskilled labor. Workers do not save, so they consume all their income in each period. At the end of each period, unskilled workers first decide whether to upgrade their skills and become students in the next period. Then all workers decide where to migrate conditional on their type.

In each period, the worker's flow utility depends on their consumption bundle:

$$c = \prod_{j=1}^{J} \left(\frac{c^j}{\gamma^j} \right)^{\gamma^j} .$$

In the expression above, the expenditure share on goods produced by industry j is γ^j and satisfies $\sum_j \gamma^j = 1$. The industry-level consumption, c^j, is a constant elasticity of substitution (CES) aggregator over N varieties available in j:

$$c^j = \left[\sum_{n=1}^{N} (c_i^j)^{\frac{\theta}{\theta+1}} \right]^{\frac{\theta+1}{\theta}} , \ \theta > 0,$$

where θ is the elasticity of substitution among varieties available in industry j.

The migration decision depends on three elements: 1) the expected lifetime utility from living in any of the J locations, 2) an idiosyncratic preference shock that follows an extreme value distribution towards each destination denoted as ε_{nt}, and 3) the skill-specific bilateral migration costs. We denote the migration costs as $\kappa^d_{ni,t}$ for a worker with type $d \in \{l, h, s\}$ to migrate from i to n at time t. We use superscript l to denote unskilled labor, h to denote skilled labor, and s to denote students. Students share the same migration costs with unskilled workers: $\kappa^l_{ni,t} = \kappa^s_{ni,t}$. Standard properties on bilateral migration cost $\kappa^d_{ni,t}$ apply: (1) $\kappa^d_{ni,t} > 0$ for $n \neq i$, (2) $\kappa^d_{ii,t} = 0$, and (3) $\kappa^d_{ni,t} \leq \kappa^d_{nj,t} + \kappa^d_{ji,t}$ for any third location j.

2.2.1 Unskilled Workers

In each period t, after production and consumption in the current location, an unskilled worker make sequential choices of skill upgrading and migration. First, they decides whether to acquire skills subject to an idiosyncratic skill shock ε_t and upgrading cost of κ_s in the unit of utility. If an unskilled worker decides not to upgrade skill, she migrates as an unskilled worker at the end of the period. If instead she chooses to upgrade her skill, she becomes a student at the same period t. Then she makes the migration choice conditional on being a student to determine where to study in period $t+1$. After fullfilling the study requirement in $t+1$, she will automatically become a skilled worker in $t+2$.

In summary, an unskilled worker living in location i at time t solves the following recursive problem:

$$
\begin{gathered}
V^l_{it} = \ln b_{it} + \ln \frac{w^l_{it}}{p_{it}} + \max_{l,s}\{\tilde{V}^l_{it} + \psi\varepsilon_{it}, \tilde{V}^s_{it} + \psi\varepsilon_{it}\} \\
\text{with } \tilde{V}^d_{it} = \max_{\{n\}}\{\xi\beta\mathbb{E}V^d_{nt+1} - \kappa^d_{ni,t} + \rho\varepsilon_{nt}\},\ d = l, s,
\end{gathered}
$$

where V^l_{it} is the value of an unskilled worker, $\tilde{V}^d_{it}$ is the continuation value conditional on being type d, and w^l_{it} is the unskilled wage rate. b_{it} is the amenity, $p_{it} = \prod_{j=1}^{J} \left(p^j_{it}\right)^{\gamma^j}$ is aggregate price index at location i, β is the discount rate, ψ governs the dispersion of skill shocks, and ρ controls the dispersion of mobility shocks.

In order to avoid all workers being skilled ones in steady state, we introduce an i.i.d exogenous exit shock so that each individual has $\xi \leq 1$ probability of surviving into the next period. A non-surviving worker in city i is replaced by an unskilled new worker in $t+1$ at the same location.

The idiosyncratic skill shocks ε_{it} are assumed to be i.i.d across location and time. The mobility shocks ε_{nt} are i.i.d across types of workers, locations, and time. Both shocks follow the Gumbel distribution with the same cumulative distribution function (CDF): $F(\varepsilon) = e^{e^{(-\varepsilon-\bar{\gamma})}}$, where $\bar{\gamma}$ is the Euler-Mascheroni constant. The term $\mathbb{E}V^d_{n,t+1}$ is the expected value of being type-d at location n in the next period, where the expectation is taken over realizations of future idiosyncratic shocks.

Define $v^d_{it} = \mathbb{E}V^d_{it}$ as the expected lifetime utility of type d workers. Applying standard properties of the Gumbel distribution solves the expected value of an unskilled worker as:

$$v^l_{it} = \ln b_{it} + \ln \frac{w^l_{it}}{p_{it}} + \psi \ln \left[\exp\left(\tilde{v}^l_{it}/\psi\right) + \exp\left(\tilde{v}^s_{it}/\psi\right)\right] \tag{1}$$
$$\text{with } \tilde{v}^d_{it} = \rho \ln \sum_{g=1}^{N} \exp\left[(\xi\beta v^d_{gt+1} - \kappa^d_{gi,t})/\rho\right],\ d = l, s.$$

As equation (1) shows, unskilled workers' skill upgrading choice depends on the expected value of being a student. Students work part-time and, at the end of the period, decide where to live in the next period as a skilled worker. Using the property of Gumbel distribution, the students' expected value is given by

$$v^s_{it} = \ln b_{it} + \ln \frac{\iota w^l_{it}}{p_{it}} - \kappa_s + \rho \ln \sum_{g=1}^{N} \exp\left[(\xi\beta v^h_{gt+1} - \kappa^h_{gi,t})/\rho\right], \tag{2}$$

where ι is the fraction of time that students devote to work and κ_s is skill upgrading cost. In other words, $1-\iota$ caputures the opportunity cost of skill upgrading.

Following the property of Gumbel distribution, the share of unskilled population who choose to upgrade their skill in location i period t is

$$D^{ls}_{it} = \frac{\exp\left[(v^s_{it+1})/\psi\right]}{\exp\left[(v^l_{it+1})/\psi\right] + \exp\left[(v^s_{it+1})/\psi\right]}, \tag{3}$$

and the migration probability for type $d = \{l, s\}$ workers from n to i is given by

$$D^d_{in,t} = \frac{\exp\left[(\xi\beta v^d_{it+1} - \kappa^d_{in,t})/\rho\right]}{\sum_{g=1}^N \exp\left[(\xi\beta v^d_{gt+1} - \kappa^d_{gn,t})/\rho\right]}, \tag{4}$$

where $1/\psi$ and $1/\rho$ capture the skill acquisition elasticity and migration elasticity repectively.

2.2.2 Skilled Workers

The setup of skilled workers is similar to that of unskilled workers, except that skilled workers do not make skill upgrading decision. Formally, a skilled worker solve the following standard discret choice problem

$$V^h_{it} = \ln b_{it} + \ln \frac{w^h_{it}}{p_{it}} + \max_{l,s} V^h_{it} + \max_{\{n\}}\{\xi\beta\mathbb{E}V^h_{nt+1} - \kappa^h_{ni,t} + \rho\varepsilon_{nt}\}.$$

Define $v^h_{it} = \mathbb{E}V^h_{nt+1}$, then the expected value is given by

$$v^h_{it} = \ln b_{it} + \ln \frac{w^h_{it}}{p_{it}} + \rho \ln \sum_{g=1}^N \exp\left[(\xi\beta v^h_{gt+1} - \kappa^h_{gi,t})/\rho\right], \tag{5}$$

and the bilateral migration probility is the same as equation (4) for $d = h$.

2.2.3 Local Labor Supply

At the end of each period, $\left(L^l_{it} + L^s_{it} + L^h_{it}\right)(1 - \xi)$ of the workers in location i exit the model and are replaced with the same number of unskilled workers. After unskilled workers making skill upgrading choices, the number of local unskilled workers that are ready to migrate is $L^l_{nt} - D^{ls}_{nt}L^l_{nt}$, where $D^{ls}_{nt}L^l_{nt}$ is population of new students in location n.

Finally, the population of unskilled workers, students, and skilled workers in each location evolves as follows:

$$L^l_{it+1} = \xi \sum_{n=1}^N D^l_{in,t}\left(L^l_{nt} - D^{ls}_{nt}L^l_{nt}\right) + \left(L^l_{it} + L^s_{it} + L^h_{it}\right)(1 - \xi), \tag{6}$$

$$L_{it+1}^{s}=\xi\sum_{n=1}^{N}D_{in,t}^{s}D_{nt}^{ls}L_{nt}^{l}, \tag{7}$$

and

$$L_{it+1}^{h}=\xi\left(\sum_{n=1}^{N}D_{in}^{h}\left(L_{nt}^{h}+L_{nt}^{s}\right)\right). \tag{8}$$

The supply of unskilled labor in location i then is $\tilde{L}_{it+1}^{l}\equiv L_{it+1}^{l}(1-D_{it+1}^{ls})+\iota L_{it+1}^{s}$. The supply of skilled labor L_{it+1}^{h} includes inflows of skilled workers and fresh graduates.

2.3 Landlords

We closely follow Kleinman et al. (2023) in modeling landlords. Landlords are immobile and have access to the financial market. With an initial endowment of capital stock, the landlords optimally choose the sequences of consumption and investments to maximize their lifetime utility. Similar to workers, at the end of each period, only a fraction ξ of landlords survive into the next period. New-born landlords replace the deceased ones and inherit their capital. The landlord's lifetime utility takes the form

$$v_{it}^{k}=\sum_{s=0}^{\infty}(\xi\beta)^{t+s}\ln c_{it+s}^{k},$$

where the superscript k denotes landlords and c_{it}^{k} is the composite consumption. The logarithm form of utility flow also implies that the intertemporal elasticity of substitution is one. Landlord's budget constraint is given by:

$$r_{it}k_{it}=p_{it}(c_{it}^{k}+k_{it+1}-(1-\delta)k_{it}),$$

where r_{it} is the rate of return on capital at time t and p_{it} is the aggregate price index defined before.

Following Kleinman et al. (2023), the logarithm utility flow implies a constant saving rate $\xi\beta$. The capital accumulation equation can thus be characterized as:

$$k_{it+1} = \xi\beta \left(1 - \delta + \frac{r_{it}}{p_{it}}\right) k_{it}. \tag{9}$$

2.4 Production

Firms at each location i and industry j specialize in one variety and operate in a perfectly competitive market, using unskilled labor (L_{it}^{lj}), skilled labor (L_{it}^{hj}), and capital (k_{it}^{j}) as inputs. The production function in location i and industry j at time t features a nested CES functional form as:

$$y_{it}^{j} = z_{it} \left[(\mu^j)^{\frac{1}{\sigma}} (L_{it}^{lj})^{\frac{\sigma-1}{\sigma}} + (1-\mu^j)^{\frac{1}{\sigma}} (L_{it}^{ej})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where z_{it} is location-specific productivity and L_{it}^{ej} is the equipped skilled labor that embodies both skilled labor and capital:

$$L_{it}^{ej} = \left[(\lambda^j)^{\frac{1}{\eta}} (k_{it}^{j})^{\frac{\eta-1}{\eta}} + (1-\lambda^j)^{\frac{1}{\eta}} (L_{it}^{hj})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}.$$

The parameters μ^j and λ^j govern the industry-specific weights of unskilled labor and capital, respectively. σ is the elasticity of substitution between unskilled and equipped skilled labor, and η is the elasticity of substitution between skilled labor and capital. We assume $\sigma > \eta$ so that capital is more complementary with skilled workers than unskilled ones. This is to capture capital-skill complementarity for all industries.[3]

Both unskilled and skilled workers are perfectly mobile across sectors within a location. The production structure implies that the unit cost of production for a variety in the industry j and location i, denoted as c_{it}^{j}, is given by:

$$c_{it}^{j} = \frac{1}{z_{it}} \left[\mu^j (w_{it}^{l})^{1-\sigma} + (1-\mu^j)(w_{it}^{e})^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{10}$$

In the above expression, w_{it}^{l} is the wage rate of an unskilled worker, and w_{it}^{e} is the unit cost of an equipped skilled labor, which can further be expressed as a function of skilled wage,

[3] For more details, see Duffy et al. (2004).

w_{it}^h, and the rental price of capital, r_{it}:

$$w_{it}^{ej} = \left[\lambda^j (r_{it})^{1-\eta} + (1-\lambda^j)(w_{it}^h)^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{11}$$

Combining solutions from the profit maximization problem and zero profit condition, we can further obtain income shares of unskilled labor (ϕ_{it}^{lj}), skilled labor (ϕ_{it}^{hj}), and capital (ϕ_{it}^{kj}) for industry j respectively:

$$\phi_{it}^{lj} = \left[1 + \frac{1-\mu^j}{\mu^j}\left(\frac{w_{it}^l}{w_{it}^e}\right)^{\sigma-1}\right]^{-1}, \tag{12}$$

$$\phi_{it}^{hj} = \left[1 + \frac{\mu^j}{1-\mu^j}\left(\frac{w_{it}^e}{w_{it}^l}\right)^{\sigma-1}\right]^{-1}\left[1 + \frac{\lambda^j}{1-\lambda^j}\left(\frac{w_{it}^h}{r_{it}}\right)^{\eta-1}\right]^{-1}, \tag{13}$$

$$\phi_{it}^{kj} = \left[1 + \frac{\mu^j}{1-\mu^j}\left(\frac{w_{it}^e}{w_{it}^l}\right)^{\sigma-1}\right]^{-1}\left[1 + \frac{1-\lambda^j}{\lambda^j}\left(\frac{r_{it}}{w_{it}^h}\right)^{\eta-1}\right]^{-1}. \tag{14}$$

We assume standard iceberg trade costs between locations. In any industry j, the price of a variety in location n imported from location i ($p_{ni,t}^j$) is

$$p_{ni,t}^j = \tau_{ni,t} c_{it}^j.$$

Lastly, as shown in the Appendix, the price index in location n and industry j, denoted as $p_{n,t}^j$, satisfies:

$$(p_{nt}^j)^{1-\theta} = \sum_{i=1}^{I} (\frac{\tau_{ni,t}}{z_{it}})^{1-\theta}\Big[\mu^j (w_{it}^l)^{1-\sigma} + (1-\mu^j)\left[\lambda^j (r_{it})^{1-\eta} + (1-\lambda^j)(w_{it}^h)^{1-\eta}\right]^{\frac{1-\sigma}{1-\eta}}\Big]^{1-\theta} \tag{15}$$

2.5 Agglomeration and Congestion

We assume that location-specific amenities and productivity depend on the population to allow for potential agglomeration and congestion externality. Specifically, the amenity in city i is determined by an exogenous location fundamental amenity, $\bar{b}_{it}$, together with population size $L_{it}^l + L_{it}^s + L_{it}^h$:

$$b_{it} = \bar{b}_{it}(L_{it}^l + L_{it}^s + L_{it}^h)^{\alpha_b},$$

where α_b captures the population elasticity of amenity. We assume $\alpha_b < 0$ to capture the negative externality led by congestion. Similarly, the local productivity is given by

$$z_{it} = \bar{z}_{it}(L_{it}^l + L_{it}^s + L_{it}^h)^{\alpha_z},$$

where $\bar{z}_{it}$ is the exogenous component of productivity and α_z is the population elasticity of productivity. We assume $\alpha_z > 0$ to capture the agglomeration effects.

2.6 Equilibrium

We define the dynamic equilibrium of the economy below.

Definition 1. Dynamic Equilibrium. Given initial conditions $\{L_{i0}^l, L_{i0}^s, L_{i0}^h, k_{i0}\}$ in each location, the dynamic equilibrium contains a sequence of location-specific prices $\{w_{it}^l, w_{it}^h, r_{it}, p_{it}\}_{t=0}^{\infty}$, quantities $\{L_{it}^l, L_{it}^s, L_{it}^h, k_{it}\}_{t=0}^{\infty}$ and value functions $\{v_{it}^l, v_{it}^s, v_{it}^h\}_{t=0}^{\infty}$, such that the following conditions hold:

1. Workers maximize their lifetime utility by making migration and skill-upgrading decisions.

2. Landlords maximize their lifetime utility by making consumption and investment decisions.

3. The evolution of population and capital is characterized as in equations (6) - (8), and (9).

4. Labor markets for unskilled and skilled workers and capital market clear in each loca-

tion.

$$w_{it}^{l} = \frac{\sum_{j=1}^{J} \phi_{it}^{lj} X_{it}^{j}}{\tilde{L}_{it}^{l}} \tag{16}$$

$$w_{it}^{h} = \frac{\sum_{j=1}^{J} \phi_{it}^{hj} X_{it}^{j}}{L_{it}^{h}} \tag{17}$$

$$r_{it} = \frac{\sum_{j=1}^{J} \phi_{it}^{kj} X_{it}^{j}}{k_{it}} \tag{18}$$

where X_{it}^{j} denotes total revenue earned in location i and industry j at time t.

5. Trade balance condition holds in all locations:

$$X_{it}^{j} = \gamma_j \sum_{n=1}^{N} \pi_{ni,t} X_{nt} = \gamma_j \sum_{n=1}^{N} \pi_{ni,t} \sum_{s=1}^{J} X_{nt}^{s}, \tag{19}$$

where $\pi_{ni,t}$ denotes the trade share between origin i and destination n at time t defined in equation (A.3) in the Appendix A.1.

The economy's steady state is a dynamic equilibrium when all the exogenous fundamentals of the economy and endogenous variables stay constant over time. We formally define the steady state of the economy as follows:

Definition 2. Steady State. A steady state of the economy is an equilibrium in which the endogenous variables are constant over time: $\{w_i^{l*}, w_i^{s*}, r_i^*, v_i^{l*}, v_i^{s*}, v_i^{h*} L_i^{l*}, L_i^{s*}, L_i^{h*}, k_i^*\}$.

3 Quantification

This section presents the details regarding the quantification of the model. We start with the basic geographic information and then provide an outline for calibrating and estimating the model's key parameters.

Each period in the model corresponds to five years, with the initial year in 2000. Our sample period is 2000-2015, during which the trade costs and migration costs change over time according to estimation from data. After the year 2015, all geographic barriers remain at the same level as 2015's. Throughout the transition path, We assume the exogenous components of local productivity and amenity are time-invariant. We quantify the model to 196 prefecture-level cities in China plus one location representing the rest of the world (ROW). This sample of 196 prefectures is the largest balanced panel in which we have access to all the needed data, as explained later. The prefectures in our sample are representative: they account for 92.8 percent of total output and 83.5 percent of the total urban population in China in the year 2000.

We map the 82 industries observed in China's 2002 Industrial Classification for National Economic Activities into four broad sectors by skill intensities and tradability: the skill- and unskill-intensive manufacturing sectors and the skill- and unskill-intensive service sectors.[4] To estimate the skill intensity at the industry level, we follow Fan (2019) and use the income share of skilled workers in each industry from the *2005 One Percent Population Survey*. We rank industries by skill intensity separately for manufacturing and service sectors and then group the industries above the median skill intensity into the skilled sectors and those below into the unskilled sectors. Tables B.3 and B.4 in the Appendix provide the detailed mapping between industries and the four sectors in the paper.

3.1 Initial Conditions

Population The initial distribution of the population by location and skill type comes from the 2000 Census. We define a skilled worker as one with a high school diploma or above.

Capital Stock We use the perpetual inventory method to estimate prefecture-level initial capital stocks in the year 2000. Following Zhang et al. (2004), we use investment data in *China City Statistical Yearbooks* from 1994 to 2000 to construct a panel dataset of capital stocks at the prefecture level. Specifically, the capital stock in location i at time t is given by:

$$K_{it} = (1-\delta)K_{it-1} + I_{it},$$

[4] Out of the 82 industries, 29 are manufacturing, and 53 are service industries

where I_{it} is the real investment observed in the data, and K_{it} is the sequence of capital stock inferred using the perpetual inventory method. We compute real investment as "Nominal Investment$_{it}$ $\times$ Investment Deflator$_{it}$", where the nominal investment is proxied using "Gross Fixed Capital Formation" from the *China City Statistical Yearbooks*; the investment deflators also come from the same source. To infer the initial capital stock, we adopt the standard approach as in Young (2003) and assume capital stock in 1994 is equal to real investment in that year divided by the depreciation rate.

Rest of the World The ROW is an aggregate of 32 OECD countries. Table B.1 in the Appendix lists all the countries included in the ROW. For each country, we observe population size by skills in 2000 from OECD Statistics, capital stocks in 2000 from Penn World Table, and the sectoral trade flow between China and each country for 2000-2005 from the World Input/Output Database (WIOD).

3.2 Geography

Trade Costs Products from the manufacturing sectors are tradable across locations, and those from the service industries are non-tradable. Within China, trade costs do not vary across tradable sectors. We use the estimation method from Ma and Tang (2020) and the mode-specific bilateral travel time from Ma and Tang (2024) to compute trade costs between Chinese prefectures for the five-year interval from 2000 to 2015. The travel time in Ma and Tang (2024) is based on freight infrastructure on road and rail networks each year during 2000-2015. The trade costs after year 2015 are fixed at the 2015's level.

We modify the methods in Ma and Tang (2024) to estimate the trade costs between Chinese prefectures and the ROW. Start with the 27 port cities in China identified in Ma and Tang (2024), we assume that all port cities face the same trade cost with the ROW in a given sector, denoted as "$\tau^j_{ROW,t}$", to be estimated later. Conditional on $\tau^j_{ROW,t}$, the trade costs between a non-port prefecture i with the ROW is given by $\tau_{i,\mathrm{port}_i} \times \tau^j_{ROW,t}$, where port_i is the nearest port to location i determined by the τ matrix within China. We allow the trade costs between China and ROW to be sector-specific, as they depend on tariff rates that vary across sectors.

We then follow Head and Ries (2001) to back out the changes in trade costs between China's port cities with the ROW from the observed trade flows, $\widehat{\tau^j_{ROW,t}} \equiv \tau^j_{ROW,t}/\tau^j_{ROW,2000}$, relative to the levels in 2000. As shown in the Appendix, the changes in trade costs can be inferred as:

$$\widehat{\tau^j_{\text{ROW},t}} = \left(\frac{\widehat{S^j}_{(\text{CN,ROW}),t} \times \widehat{S^j}_{(\text{ROW,CN}),t}}{\widehat{S^j}_{(\text{ROW,ROW}),t} \times \widehat{S^j}_{(\text{CN,CN}),t}} \right)^{-\frac{1}{2\theta}}, \tag{20}$$

where $\widehat{S^j}_{(\cdot),t}$ is the changes in trade flow in sector j between year t and the initial year. With the trade elasticity parameter θ and the observed flows, we calculate the *changes* in trade costs for each sector in the year 2005 relative to 2000 to capture trade liberalization due to China's accession to WTO. Trade costs after 2005, $\tau^j_{ROW,t>2005}$, are stay at 2005's level. Finally, we determine the initial levels of trade costs in 2000, denoted as $\tau^j_{ROW,2000}$, by inverting the model in the initial spatial equilibrium and precisely matching the observed trade costs in that year.[5] With the estimated $\tau^j_{ROW,t}$, we have complete trade costs matrices across all locations in all sample years.

Migration Costs Workers can migrate across prefectures within China subject to type-specific friction, and no international immigration is possible between China and the ROW. We discipline the migration frictions in China as follows.

Our estimation procedure relies on two data sources: 1) the *2005 One Percent Population Survey*, and 2) the passenger transportation network from Ma and Tang (2024). The population survey allows us to compute the share of migrants in prefecture g with hukou from prefecture i for skill type d as a fraction of the population in location i, denoted as $\bar{D}^d_{gi,t}$. For simplicity, we assume away the skill upgrading in estimating migration frictions. In Appendix B.5, we establish the following relation in steady state between $\bar{D}^d_{gi}$ and our

[5]Head and Ries (2001) directly inferred the trade costs between countries each year. We cannot directly adopt their methods because our model features a rich internal geography inside China, while Head and Ries (2001) abstracted away from internal geography. As a result, the levels of $\{\tau^j_{ROW,t}\}$ inferred using Head and Ries (2001) do not exactly align the observed and the model-simulated trade shares at the aggregate level. To ensure consistency between the baseline model and the data, we only use their methods to infer the *changes* in trade costs across years and rely on inverting the model in the initial equilibrium to back out the initial levels of trade costs.

model-predicted migration share D^d_{gi}:

$$\bar{D}^d_{gi} = \frac{D^d_{gi}}{1 - D^d_{gg}},$$

where D^d_{gi} is the model-consistent migration probability that depends on option values and the migration costs:

$$D^d_{gi} = \frac{\exp\left[(\beta v^d_{gt+1} - \kappa^d_{gi})/\rho\right]}{\sum_{n=1}^{N} \exp\left[(\beta v^d_{nt+1} - \kappa^d_{ni})/\rho\right]}.$$

Double differencing the relation above removes the option value from the expression and leads to:

$$\frac{\bar{D}^d_{gi}}{\bar{D}^d_{ii}} \frac{\bar{D}^d_{ig}}{\bar{D}^d_{gg}} = \frac{D^d_{gi}}{D^d_{ii}} \frac{D^d_{ig}}{D^d_{gg}} = \exp\left[-\frac{1}{\rho}(\kappa^d_{gi} + \kappa^d_{ig})\right]. \tag{21}$$

We further assume that the bilateral migration cost is the sum of the bilateral travel cost and the entry barrier of the destination location:

$$\kappa^d_{gi} = \kappa^d_g + \bar{\kappa}_{gi},$$

where $\bar{\kappa}_{gi} = \bar{\kappa}_{ig}$ is symmetric travel cost between location i and g that depends on the passenger travel infrastructure, and κ^d_g is type-specific entry barrier for entering location g. We interpret the entry barriers as policy restrictions such as the hukou registration. Conditional on the symmetric travel costs from Ma and Tang (2024), estimating migration costs is equivalent to estimating entry barriers for all locations. Taking stock, the estimation equation becomes:

$$\begin{aligned} \frac{\bar{D}^d_{gi}}{\bar{D}^d_{ii}} \frac{\bar{D}^d_{ig}}{\bar{D}^d_{gg}} &= \exp\left[-\frac{1}{\rho}(\kappa^d_g + \kappa^d_i + 2\bar{\kappa}_{gi})\right] \\ \frac{\bar{D}^d_{gi}}{\bar{D}^d_{ii}} \frac{\bar{D}^d_{ig}}{\bar{D}^d_{gg}} \exp\left(\frac{2\bar{\kappa}_{gi}}{\rho}\right) &= \exp\left[-\frac{1}{\rho}\left(\kappa^d_g + \kappa^d_i\right)\right]. \end{aligned} \tag{22}$$

Given travel costs and migration elasticity parameter ρ, we estimate the time-invariant entry barriers κ^d_g for each location and skill type using Poisson regression based upon equation (22).

Note that we still allow bilateral travel time varies over time, as it depends on domestic infrastructure conditions. The final bilateral migration frictions in each year is equal to the destination entry barrier plus travel costs in that year.

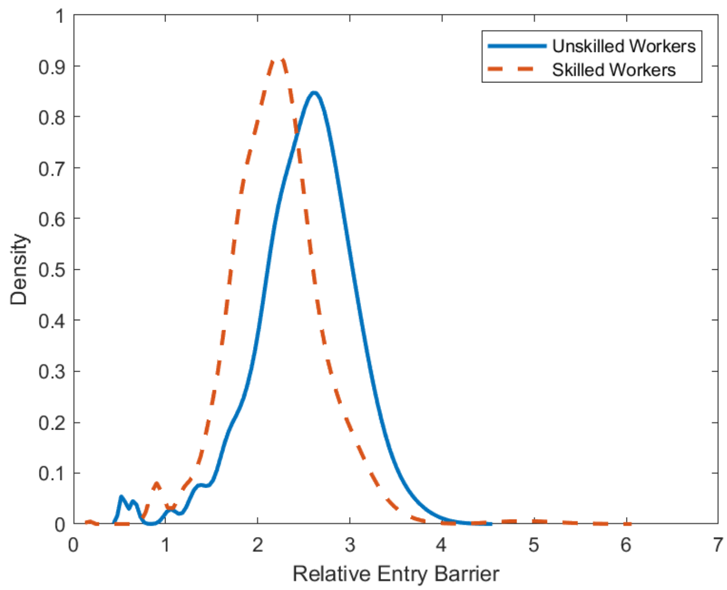


Figure 1: Distribution of Entry Barriers

Notes: This figure shows the histogram of the estimated entry barriers for unskilled and skilled workers. Entry barriers reported here are estimated using PPML and normalized by the average bilateral travel cost between any city pair in 2000 China.

Our estimation reveals that the migration frictions are substantial and, on average, higher for unskilled workers than for skilled ones. Figure 1 presents the histogram of entry barriers for unskilled and skilled workers across locations. In the figure, we normalize the entry barriers by the average bilateral geographic travel cost in China. The migration costs are formidable, equivalent to 2.2 times of average travel costs for skilled workers or 2.5 times for unskilled workers. The higher migration costs unskilled workers face come from the discriminative hukou policy.

3.3 Parameterization

We discipline all the other parameters in one of the three ways. Some of the parameters were externally determined based on the estimates in the literature; Some parameters come from inverting the model in the initial static equilibrium. Lastly, the parameters affecting population distribution were calibrated along the transition path. In the rest of the section, we briefly discuss the quantification strategy of these parameters.

Pre-determined Parameters We choose trade elasticity $\theta = 5$ from Costinot and Rodríguez-Clare (2014). We assume a five-year discount rate of $\beta = 0.86$, consistent with an annual interest rate of 3 percent. We set the migration elasticity parameter $\rho = 3\beta$, following Kleinman et al. (2023). From the urban literature, we assume an agglomeration elasticity of $\alpha_z = 0.1$ from Redding and Turner (2015) and a congestion elasticity of $\alpha_b = -0.3$ from Allen and Arkolakis (2022). The parameters that govern the complementarity between skill and capital stock come from the macroeconomic literature: we take the elasticities of substitution $\sigma = 2$ and $\eta = 1$ from Duffy et al. (2004). Finally, according to the World Bank, the average annual mortality rate in China during 2000-2020 is 0.7 percent, suggesting a five-year survival rate of $\xi = 0.965$.

Table 1: External Calibrated Parameters

Name	Value	Source	Description
α_z	0.1	Redding and Turner (2015)	Agglomeration elasticity
α_b	-0.3	Allen and Arkolakis (2022)	Congestion elasticity
β	0.86	-	Five-year discount factor
θ	5	Costinot and Rodríguez-Clare (2014)	Trade elasticity
ρ	3β	Kleinman et al. (2023)	Inverse of migration elasticity
ψ	5.74	Hu and Ma (n.d.)	Inverse of upskilling elasticity
σ	2	Duffy et al. (2004)	EoS between l and e
η	1	Duffy et al. (2004)	EoS between h and k
δ	0.41	Zhang et al. (2004)	Five-year capital depreciation rate from 0.1 annual rate
τ_{ni}	-	Ma and Tang (2024)	Bilateral trade cost
γ^j	-	China 2002 IO table	Sectoral consumption share
ξ	0.965	World Bank	Five-year mortality rate of $1-\xi$

Notes: This table reports the results of calibrated parameters in the model. These parameters either come from the literature or data.

Inverting the Initial Equilibrium A subset of parameters, $\{\bar{z}_i, \mu^j, \lambda^j, \tau^j_{ROW,2000}\}$, are calibrated so that the initial static equilibrium matched the observed economic conditions in 2000. As is common in the dynamic spatial models, we do not need to assume that the model in 2000 is in a steady state. Instead, we only need to assume that the initial static equilibrium is on a transition path toward a future steady state.

The exogenous component of prefecture-level fundamental productivity, $\bar{z}_i$, is calibrated to match prefecture-level GDP share in 2000. We normalize the fundamental productivity in the first location (Beijing) to unity so that $\bar{z}_1 = 1$. The parameters that capture the relative importance of unskilled workers and capital in production in each industry, μ^j and λ^j, are calibrated to match the sectoral income shares for unskilled workers and capital in the data, respectively. To allow for technology differences between the ROW and China, we estimate these parameters separately for China and the ROW. In the case of China, the sector-level income share of skilled workers comes from *2005 One Percent Population Survey*, and the share of capital in the value-added comes from China's Input-Output table in 2002. In the case of ROW, the skilled workers' income shares in each sector are computed from the IPUMS One Percent Sample. The U.S. Input-Output Table in 2007 was used to obtain capital income shares.

Table 2 shows the calibrated results of weights on unskilled workers and capital in production function for China and the ROW. Unsurprisingly, unskilled sectors put more weight on unskilled workers than skilled workers. Moreover, in China, capital takes up higher weights in unskilled manufacturing sectors ($\lambda^j = 0.83$) than in skilled ones ($\lambda^j = 0.75$). This pattern reflects the fact that in the 2000s, capital-intensive industries in China, such as primary metal, were also more reliant on unskilled workers than skilled ones. On the contrary, the skilled sector is more capital-intensive than the unskilled sector in the ROW. These estimation results subsequently imply the pattern of comparative advantage in the quantitative analysis presented later. Considering that 1) the ROW is relatively more abundant in skilled workers and capital in the data, and 2) the skilled sector is capital-intensive in the ROW's production function, as per our estimation, the ROW specializes in the skilled sector when trading with China.

Lastly, as discussed above, we invert the model at the initial static equilibrium to back out the initial trade costs between ROW and Chinese port prefectures in levels, $\tau^j_{ROW,2000}$.

Amenities and Skill Upgrading Costs The last group of parameters is calibrated on the transition path, conditional on the abovementioned parameters. These parameters are

Table 2: Calibrated Production Function

Panel (a): China

Weights	Unskilled Manu.	Skilled Manu.	Unskilled Service	Skilled Service
μ^j	0.18	0.08	0.15	0.02
λ^j	0.83	0.75	0.73	0.59

Panel (b): ROW

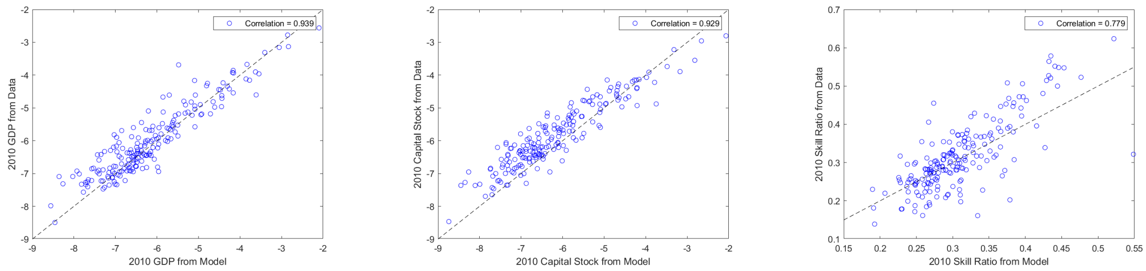
Weights	Unskilled Manu.	Skilled Manu.	Unskilled Service	Skilled Service
μ^j	0.04	0.02	0.04	0.01
λ^j	0.39	0.57	0.42	0.55

Notes: This table reports the results of production weights in four sectors for China and the ROW. The weights are calibrated in the initial static equilibrium by targeting sector-level factor income shares. $\mu \in [0, 1]$ is the weight on unskilled workers and $\lambda \in [0, 1]$ is the weight on capital.

the skill upgrading cost κ_s and location-specific amenities $\{\bar{b}_i\}$. Specifically, κ_s is chosen to match the aggregate skill ratio of 0.36 in the year 2010, as indicated by the population Census in China that year. Our calibrated skill upgrading cost is 58 percent of the average lifetime utility among unskilled workers in the initial period. The high upgrading costs reflect two patterns in the data: on the one hand, the skill premium is high in the data at 1.44 in the year 2005. On the other hand, the supply of skills had been low during the same period. Intuitively, the skill upgrading costs encompass not just the financial costs of acquiring a high school or college education but also the fierce selection induced by the strict quota system in Chinese secondary and tertiary education, manifested through the High School or College Entry Exams.

The location fundamental amenity, $\{\bar{b}_i\}$, is calibrated to match the population share of each prefecture in the year 2010. Unlike the location fundamental productivity that only requires solving the initial static equilibrium, simulating the population distribution requires solving the entire transition path in levels. Intuitively, the population distributions in any $t > 1$ are functions of future option values of each location and, therefore, require information on the entire transition path.

Model Fit The quantification strategy described above aligns reasonably well with the untargeted data moments. Figure 2 compares the model-predicted spatial distribution of total output, capital stock, and skill ratio with their data counterparts, none of which is our calibration target. The model matches the data well, showing correlations ranging from 0.65 to 0.85.



(a) GDP (b) Capital Stock (c) Skill Ratio

Figure 2: Model Fit

Notes: These figures compare the baseline model simulation with the data. Each dot represents a prefecture in China, and the black dotted line is the 45-degree line. All the variables in the model and the data refer to the cross-section in the year 2010. Variables in panel (a)-(b) are in the logarithmic functions.

4 Quantitative Analysis

We first consider two hypothetical uniform economic shocks and quantify the aggregate and spatial impacts of those shocks. Those counterfactual experiments are aimed to illustrate how the impacts of shocks depend on our model mechanisms, as a uniform shock is much more straightforward than a historical shock that changes fundamentals unevenly across space. To explore the role of model mechanisms, we consider four different model setups: the benchmark model described before, the model with skill acquisition but no capital accumulation, the model with endogenous capital accumulation but no upskilling, and the bare-bone model without both capital accumulation and skill acquisition. Then we implement counterfactual simulation and evaluate the shocks' impacts for each specified model. As there are four different models, for the same economic shock, we run four sets of counterfactual experiments. After understanding how the model works, we quantitatively analyze two economic shocks that happened in early 2000 China: China's ascension to the WTO and its large-scale investment in domestic infrastructure.

We differentiate three different model specifications from the benchmark model, each used to highlight one mechanism. In the "with upskilling" simulation, unskilled workers are allowed to upskill as in the baseline model, but capital stock in each location is fixed at the initial level. In particular, we set the landlords' investment to cover the depreciated capital in each period, thereby fixing the level of capital stock. In the "with capital" simulation, capital accumulates endogenously, but the total skill ratio in China is fixed by assuming the following two conditions: (1) skill upgrading cost κ_s is infinite; (2) the same amount of workers will replace those exiting the model for each type by adjusting the labor supply equation (6)-(8) as:

$$
\begin{aligned}
L_{it+1}^{l} &= \sum_{n=1}^{N} D_{in,t}^{l} \left(L_{nt}^{l} - D_{nt}^{ls} L_{nt}^{l} \right) \\
L_{it+1}^{s} &= \sum_{n=1}^{N} D_{in,t}^{s} D_{nt}^{ls} L_{nt}^{l} \\
L_{it+1}^{h} &= \sum_{n=1}^{N} D_{in}^{h} \left(L_{nt}^{h} + L_{nt}^{s} \right).
\end{aligned}
$$

In the "basic model" simulation, both previous restrictions apply so that local capital stocks and China's total skill ratio are constant.

4.1 Hypothetical Shocks

4.1.1 A Uniform Productivity Shock

We first consider a permanent productivity shock that increases all Chinese cities' local productivities $\bar{z}_i$ by 20 percent from the year 2000. We evaluate the aggregate and spatial impacts of such productivity increase under different model specifications.

Table 3 reports the aggregate impacts on production factors, skill premium, and different welfare measures in the steady state. We use changes in real wage, total output, and total consumption[6] to measure welfare gains. In the basic model simulation, in which we shut

[6]The consumption change is defined as Δ such that the counterfactual utility of unskilled worker $v_{it}^{l'} = \sum_{t=1}^{\infty} (\xi\beta)^t \log \left((1+\Delta) c_{it}^{l} \right) = \sum_{t=1}^{\infty} (\xi\beta)^t \log (1+\Delta) + \sum_{t=1}^{\infty} (\xi\beta)^t \log \left(c_{it}^{l} \right) = \sum_{t=1}^{\infty} (\xi\beta)^t \log (1+\Delta) + v_{it}^{l}$, where v_{it}^{l} is the baseline utility of unskilled worker. As unskilled worker utility incorporates future student utility and thus skilled worker utility, the resulting consumption change represents the total welfare change.

down both physical and human capital accumulation, the shock drives up aggregate welfare by 20% percent, the exactly same amount as the productivity increase.

Comparing the impacts of productivity shock across different model setups, we find several interesting results shown in the table. Firstly, allowing capital accumulation alone substantially augments welfare improvement and intensifies between-skill inequality: the welfare gains measured by real wage changes almost double (from 20 to 36 percent) for unskilled workers and triple for skilled workers (from 20 to 67 percent), and the average skill premium increases by 21 percent. The welfare amplification effect is due to the accelerated rate of capital accumulation, which arises from the fact that the productivity boom increases the real return on investment. Meanwhile, more capital stocks raise the return on skill due to capital-skill complementarity, driving up the average skill premium.

Secondly, conditional on capital accumulation, allowing upskilling magnifies the shock-driven capital growth and welfare impacts further, but attenuates the skill premium's rise. The attenuation of skill premium change is a result of two competing forces. On the one hand, the productivity shock increases the total skill ratio (by 2 percent) once workers are allowed to upskill, mainly due to the faster capital accumulation. This increased supply of skills weakens the shock-induced skill premium increase. On the other hand, more skilled workers also encourage more capital stock. As shown from row 3 and row 1 in table 3, the response in total capital stock changes from 85 percent to 95 percent increase. This additional boost in capital stock raises the return on skill. In the end, the former force dominates the latter, diminishing the positive impact on skill premium from 21 to 18 percent.

Thirdly, in the absence of capital accumulation, whether incorporating skill acquisition does not change the aggregate impacts of productivity shock. Most surprisingly, the productivity shock drives almost no upskilling even workers are allowed to do so. This suggests that the response of skill acquisition is closely related to capital accumulation adjustment.

The second and the third results together imply that our model exhibits a strong interaction effect between capital accumulation and skill acquisition. When both factors' accumulation are incorporated, they reinforce each other's response to the productivity shock, augmenting the welfare impacts. As shown in the first two columns in table 3, more capital accumulation encourages more skill upgrading, and vice versa. This interaction between factor accumulation has important implications for quantifying impacts on other economic outcomes. For example, consider the impacts on unskilled workers' real wages. From the basic model to the full model simulation, capital accumulation and upskilling together contribute to $48 - 20 = 28$ percent of additional impact. Allowing capital accumulation alone only explains 57 percent [7] of such additional impact, and upskilling explain 0 percent. Therefore, the remaining 43 percent of the additional impacts is due to the interactive response of factor accumulations. Our finding also has an important implication for quantifying the impact on skill premium: allowing capital accumulation alone overestimates the impact and allowing upskilling alone underestimates it. Therefore, both factor accumulation channels are crucial to correctly quantify the impacts on skill premium. Ignoring either mechanism will underestimate the welfare impact and bias the impact evaluation on skill premium.

Table 3: Aggregate Impacts of Uniform Productivity Shock

	%Changes in Steady State						
	Capital	S.R.	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	95.33	2.22	47.94	75.17	17.79	91.63	56.77
With Upskilling	-	0.00	20.00	20.00	0.00	20.00	20.00
With Capital	85.03	-	36.10	67.11	20.58	75.82	36.50
Basic Model	-	-	20.00	20.00	0.00	19.98	20.01

Notes: This table reports the steady state % changes of aggregate economic outcomes in China induced by a uniform 20% increase in productivity under different model specifications. From left to right economic outcomes are total capital stock, total skill ratio, real unskilled wage, real skilled wage, average skill premium, total GDP, and consumption equivalence. The "Full Model" is the baseline model; 'With Upskilling' refers to the model with skill acquisition but constant local capital stock; 'With Capital' refers to the model with endogenous capital accumulation but skill upgrading cost is infinite: $\kappa_s = \infty$; 'Basic Model' refers to the one with constant capital stock and $\kappa_s = \infty$. The real unskilled (skilled) wage is a weighted average with the weight of each city being the share of local unskilled (skilled) labor. GDP is the China's total output $\sum_{i=1}^{N-1} X_i^*$. C.E. is $100\% \times \Delta$ as defined before.

Next, we evaluate how spatial distributions of the productivity shock's impacts depend on factor accumulations. Table 4 reports how the local impacts on production factors, skill premium, and welfare are distributed across space within China. we use the across-location standard deviation and the range to measure the dispersion of spatial impacts. As rows 2 and 4 in the table show, the uniform productivity shock generates uniform spatial impacts given

[7] $(36 - 20)/28 \times 100\% = 57\%$

fixed local capital stocks. Adding capital accumulation induces strong heterogeneous spatial impacts, and incorporating upskilling in addition further promotes spatial heterogeneity. The reason behind these enlarged spatial heterogeneities is that initially more productive cities now are able to accumulate capital faster than undeveloped cities. Due to the faster capital accumulation, those productive cities also attract more migrants as marginal returns on labor increase. Eventually, they reap a larger gain from the productivity shock than less-productive cities. Allowing both factor accumulation strengthens their initial advantages even more due to the interaction effect, resulting in even greater spatial heterogeneity as suggested by larger standard deviations and range in the first row in table 4.

Table 4: Spatial Dispersion of Impacts of Uniform Productivity Shock

	Standard Deviation of Changes in Steady State							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	17.16	0.39	6.11	3.94	7.47	2.08	0.36	2.16
With Upskilling	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
With Capital	15.06	1.78	4.37	3.54	5.79	1.22	0.31	1.55
Basic Model	0.00	0.05	0.06	0.02	0.02	0.03	0.00	0.04

	Max %Changes - Min %Changes in Steady State							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	92.90	3.05	34.11	19.49	39.41	12.28	2.22	22.12
With Upskilling	0.00	0.00	0.04	0.01	0.02	0.01	0.00	0.03
With Capital	84.70	9.50	25.11	19.34	31.48	6.74	2.24	9.67
Basic Model	0.00	0.69	0.81	0.28	0.31	0.49	0.05	0.57

Notes: This table reports the % changes of aggregate economic outcomes in China induced by a uniform 20% increase in productivity under different model specifications. From left to right economic outcomes are total capital stock, total skill ratio, real unskilled wage, real skilled wage, average skill premium, total GDP, and consumption equivalence. The "Full Model" is the baseline model; 'With Upskilling' refers to the model with skill acquisition but constant local capital stock; 'With Capital' refers to the model with endogenous capital accumulation but skill upgrading cost is infinite: $\kappa_s = \infty$; 'Basic Model' refers to the one with constant capital stock and $\kappa_s = \infty$. The real unskilled (skilled) wage is a weighted average with the weight of each city being the share of local unskilled (skilled) labor. GDP is the China's total output $\sum_{i=1}^{N-1} X_i^*$. C.E. is 100% $\times\ \Delta$ as defined before.

4.1.2 A Uniform Infrastructure Improvement

In this section, we consider a permanent and uniform improvement in infrastructure starting from 2015 that will reduce domestic bilateral trade costs by 20 percent. Specifically, the counterfactual domestic trade costs $\tau^{'}_{ni,t}$ is given by $\tau^{'}_{ni,t} = 1 + (100\% - 20\%)(\tau_{ni,t} - 1)$ for the year 2015 and afterward, where $\tau_{ni,t}$ is the baseline trade cost. Table 5 summarizes the steady-state aggregate impacts on production factors, skill premium, and various welfare measures.

In the basic model simulation, the infrastructure improvement increases the average real wage of both skilled and unskilled workers by around 1.2 percent. The total welfare, measured by consumption change, also increases by 1.2 percent. The change in connectivity is also skill-neutral in the basic model, as it leaves a negligible impact on skill premium.

However, as shown in the third row in table 5, incorporating capital accumulation significantly enlarges the welfare impacts and renders the infrastructure shock skill-biased. More specifically, the impact of unskilled real wage increases from 1.2 percent to 1.9 percent, a 58 percent additional impact contributed by capital accumulation. The impact on skilled real wage amplifies even larger, from 1.3 percent to 3.3 percent. These larger welfare impacts are again due to faster capital accumulation driven by the infrastructure shock. Furthermore, the shock increases skill premium by 1.2 percent, suggesting an unequal gain from infrastructure improvement. Intuitions behind this distributional impact are as follows: as the infrastructure improvement reduces the costs of sourcing varieties from other locations (p_{it}), and hence the investment cost, it promotes capital accumulation. As shown in the table, the infrastructure improvement increases total capital stock by 3.6 percent once capital is able to accumulate. More capital stocks increase skilled wages relatively more due to capital-skill complementarity. Therefore, a skill-neutral infrastructure shock in the basic model becomes skill-biased once we incorporate endogenous capital adjustment.

We again find strong evidence of interactive responses of factor accumulation to a given shock. As shown in table 5, allowing upskilling alone barely changes the aggregate impacts (from row 4 to row 2), but it exerts strong influences on welfare gains and skill premium changes conditional on endogenous capital accumulation (from row 3 to row 1). Specifically,

Table 5: Aggregate Impacts of Uniform Infrastructure Improvement

	%Changes in Steady State						
	Capital	S.R.	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	3.17	0.11	2.47	3.53	1.05	3.51	1.36
With Upskilling	-	0.01	1.20	1.26	0.06	0.79	1.22
With Capital	3.57	-	1.91	3.28	1.24	3.45	1.27
Basic Model	-	-	1.16	1.26	0.08	0.82	1.21

Notes: This table reports the steady state % changes of aggregate economic outcomes in China induced by a uniform infrastructure shock under different model specifications. From left to right economic outcomes are total capital stock, total skill ratio, real unskilled wage, real skilled wage, average skill premium, total GDP, and consumption equivalence. The "Full Model" is the baseline model; 'With Upskilling' refers to the model with skill acquisition but constant local capital stock; 'With Capital' refers to the model with endogenous capital accumulation but skill upgrading cost is infinite: $\kappa_s = \infty$; 'Basic Model' refers to the one with constant capital stock and $\kappa_s = \infty$. The real unskilled (skilled) wage is a weighted average with the weight of each city being the share of local unskilled (skilled) labor. GDP is the China's total output $\sum_{i=1}^{N-1} X_i^*$. C.E. is $100\% \times \Delta$ as defined before.

adding upskilling conditional on investment further enlarges the welfare impacts but dampens skill premium increases. The attenuation in skill premium's increase is due to upskilling balancing the skill supply in response to the shock, as many unskilled workers are now able to upgrade their skill type to enjoy the skill premium rise. However, in the absence of capital accumulation, skill upgrading barely affects the skill ratio and skill premium. In the case of unskilled workers' real wage changes, we find that the interaction effect between factor accumulation contributes to 40 percent[8] of the total welfare gain amplification from the basic to full model simulation.

In table 6, we further show that the spatial heterogeneity of the impacts also critically depends on the factor accumulation. Compared to the full model simulation, the basic model simulation exhibits much smaller spatial variations of benefits from infrastructure improvement. Adding capital accumulation significantly differentiates the top winner and the last winner. For example, the top winner only gains 2 percent more consumption than the last winner in basic model simulation, but the gap widens to 4.7 percent with capital accumulation. Further incorporating upskilling enlarges spatial variation slightly, but adding

[8] Capital accumulation explains $(1.91 - 1.16)/(2.47 - 1.16) \times 100\% = 57\%$ of the total amplification, skill acquisition contributes $(1.20 - 1.16)/(2.47 - 1.16) \times 100\% = 3\%$, and the interaction between capital and upskilling contributes the remaining 40%

upskilling alone almost does not affect it, suggesting an interaction effect between capital accumulation and skill acquisition.

Table 6: Spatial Dispersion of Impacts of Uniform Infrastructure Improvement

	Standard Deviation of Changes in Steady State							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	3.09	0.17	1.81	1.02	1.29	0.35	0.19	0.48
With Upskilling	0.00	0.04	0.48	0.44	0.28	0.18	0.01	0.23
With Capital	2.96	0.29	1.61	0.99	1.17	0.24	0.19	0.44
Basic Model	0.00	0.19	0.62	0.41	0.34	0.08	0.02	0.21

	Max %Changes - Min %Changes in Steady State							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	26.14	1.70	15.94	8.91	10.30	2.07	1.72	6.32
With Upskilling	0.00	0.19	2.61	2.29	1.41	1.09	0.08	2.08
With Capital	22.78	2.83	12.81	7.53	8.30	2.33	1.60	4.69
Basic Model	0.00	1.38	3.48	2.14	1.68	0.48	0.15	1.96

Notes: This table reports the % changes of aggregate economic outcomes in China induced by a uniform infrastructure shock under different model specifications. From left to right economic outcomes are total capital stock, total skill ratio, real unskilled wage, real skilled wage, average skill premium, total GDP, and consumption equivalence. The "Full Model" is the baseline model; 'With Upskilling' refers to the model with skill acquisition but constant local capital stock; 'With Capital' refers to the model with endogenous capital accumulation but skill upgrading cost is infinite: $\kappa_s = \infty$; 'Basic Model' refers to the one with constant capital stock and $\kappa_s = \infty$. The real unskilled (skilled) wage is a weighted average with the weight of each city being the share of local unskilled (skilled) labor. GDP is the China's total output $\sum_{i=1}^{N-1} X_i^*$. C.E. is $100\% \times \Delta$ as defined before.

In summary, in this section, we use two hypothetical economic shocks to illustrate how physical and human capital accumulation determine the aggregate and spatial impacts of them. The results show that the impacts critically depend on both capital accumulation and skill acquisition. Omitting either mechanism will bias the quantification results. More importantly, there is an interaction effect at present only when both factor accumulation channels are modeled. With these results in mind, in the next section, we will look at some realistic shocks that happened in early 2000 China and quantify their impacts based on our models.

4.2 Impacts of Trade Liberalization

In this part, we discuss the aggregate and the spatial impacts of trade in the context of China's WTO accession. Specifically, we compare the baseline economy with observed trade liberalization after the WTO accession to a counterfactual economy where the trade costs between China and the ROW were kept at the pre-WTO levels in the year 2000. We run this counterfactual experiment separately for each model setup.

Since China is unskilled-abundant relative to the ROW in the early 2000s, it has a comparative advantage in the unskilled manufacturing sector. Thus we expect that China's trade liberalization benefits unskilled workers more than skilled workers because of the Stopler-Samuelson theorem. In the basic model, as shown in row 4 in table 7, trade liberalization brings positive but highly unequal welfare gains across skill types. The unskilled real wage increases by 2.4% percent but the skilled one only increases by 0.7%, reducing the skill premium by 1.6% percent. This result is consistent with the prediction from the Stopler-Samuelson theorem.

Table 7: Aggregate Impacts of Trade Liberalization

	%Changes in Steady State						
	Capital	S.R.	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	3.73	-0.05	3.48	3.09	-0.31	12.27	3.28
With Upskilling	-	-0.17	1.99	0.72	-1.25	8.79	1.59
With Capital	4.76	-	4.23	3.85	-0.19	13.31	4.17
Basic Model	-	-	2.34	0.68	-1.59	9.91	2.35

Notes: This table reports the steady state % changes of aggregate economic outcomes in China induced by trade liberalization under different model specifications. From left to right economic outcomes are total capital stock, total skill ratio, real unskilled wage, real skilled wage, average skill premium, total GDP, and consumption equivalence. The "Full Model" is the baseline model; 'With Upskilling' refers to the model with skill acquisition but constant local capital stock; 'With Capital' refers to the model with endogenous capital accumulation but skill upgrading cost is infinite: $\kappa_s = \infty$; 'Basic Model' refers to the one with constant capital stock and $\kappa_s = \infty$. The real unskilled (skilled) wage is a weighted average with the weight of each city being the share of local unskilled (skilled) labor. GDP is the China's total output $\sum_{i=1}^{N-1} X_i^*$. C.E. is $100\% \times \Delta$ as defined before.

When we include skill acquisition, the positive welfare gain becomes smaller: the impact on consumption drops from 2.4 percent to 1.6 percent. The reason is that allowing upskilling weakens China's comparative advantage in the unskilled manufacturing sector, as China now is less unskilled-abundant than it would be if unskilled workers were not allowed to upskill. But relative to the ROW, China still has a comparative advantage in the unskilled sector. Consistent with the Stopler-Samuelson theorem, trade liberalization now discourages skill upgrading, reducing the total skill ratio in China by 0.2 percent. Due to the endogenous adjustment of skill supply to the negative shock in the skilled sector, the trade's impact on skill premium is smaller compared to that in the basic model simulation, changing from -1.6 percent to -1.3 percent.

Next, adding back capital accumulation but no upskilling yields a much higher welfare gain from trade liberalization. The unskilled real wage increases by 4.2% percent. The skilled real wage increases by 3.8%, a more than fivefold rise from 0.7% percent in the basic model simulation. The result is very intuitive. With endogenous capital, trade liberalization reduces the cost of sourcing investment goods and thus increases total capital stock. Due to capital-skill complementarity, this positive impact on capital stock substantially improves skilled workers' welfare gain. More interestingly, trade liberalization only decreases skill premium by 0.2 percent under capital accumulation, suggesting that capital accumulation counteracts and almost offsets the Stopler-Samuelson force in determining trade's impact on skill premium.

Finally, including both capital accumulation and upskilling generates an interaction effect. From the first two columns in table 7, capital accumulation alleviates skill downgrading driven by trade liberalization, and the lower skill ratio also diminishes the positive impact on capital stock. In the end, trade liberalization induces a moderate increase in welfare and a slight decrease in skill premium.

Although trade liberalization creates aggregate welfare improvement in China, the local gains are highly unequal across regions, and the degree of inequality especially depends on our model mechanism. Table 8 reports cross-city inequality measures of economic benefits from trade liberalization. The main message here is that endogenous factor accumulation significantly widens the benefit gaps across cities. Coastal cities in China, due to their geographic closeness to the ROW, pick larger gains from trade liberalization than inland cities. Incorporating physical and human capital accumulation further reinforces their geographic advantage, as trade liberalization allows them to source cheap varieties from the ROW and accumulate more capital stocks.

Table 8: Spatial Dispersion of Trade Liberalization's Impacts

	Standard Deviation of Changes in Steady State							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	5.15	0.13	2.81	1.46	1.97	0.55	0.27	0.59
With Upskilling	0.00	0.06	0.47	0.49	0.26	0.23	0.07	0.24
With Capital	4.99	0.53	2.42	1.48	1.83	0.40	0.32	0.63
Basic Model	0.00	0.30	0.65	0.44	0.35	0.13	0.17	0.21

	Max %Changes - Min %Changes in Steady State							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	26.26	1.36	15.04	6.92	10.04	3.64	1.42	2.82
With Upskilling	0.00	0.32	2.46	2.51	1.32	1.36	0.37	1.24
With Capital	26.43	2.79	13.62	7.70	9.55	3.30	2.00	3.25
Basic Model	0.00	1.57	3.52	2.38	1.80	0.85	0.93	1.10

Notes: This table reports the % changes of aggregate economic outcomes in China induced by liberalization under different model specifications. From left to right economic outcomes are capital stock, skill ratio, real unskilled wage, real skilled wage, skill premium, GDP, and consumption equivalence. The "Full Model" is the baseline model; 'With Upskilling' refers to the model with skill acquisition but constant local capital stock; 'With Capital' refers to the model with endogenous capital accumulation but skill upgrading cost is infinite: $\kappa_s = \infty$; 'Basic Model' refers to the one with constant capital stock and $\kappa_s = \infty$. The real unskilled (skilled) wage is a weighted average with the weight of each city being the share of local unskilled (skilled) labor. GDP is the China's total output $\sum_{i=1}^{N-1} X_i^*$. C.E. is $100\% \times \Delta$ as defined before.

In particular, as shown in the table 8, the top winner from trade liberalization accumulates 26 more percent of capital than the last winner under the full model simulation. Consequently, the trade shock induces a larger migrant (also skilled migrant) inflow towards coastal cities and welfare gains in the full model simulation than in the basic model simulation. For example, compare Dalian, a coastal city and one of the top winners, and Chengdu, an inland large city and one of the last winners of trade liberalization. In the basic model simulation, Dalian attracts 1.3 percent more migrants and consumes 2.8 percent more due to the trade liberalization, while Chengdu loses 1.1 percent of its workforce and consumes only 2.0 percent more. These unequal gains in consumption and trade-induced migration pattern from inland to coast already suggest coastal cities are the main beneficiaries of trade liberalization. But factor accumulations significantly widen the unequal gains from trade.

In the full model simulation, the trade-induced workforce change is a striking 9.8 percent increase in Dalian, and a 5.4 percent drop in Chengdu; local consumption increases in Dalian become 5.2 percent and in Chengdu is 2.1.

4.3 Impacts of Infrastructure Investment

During the early 2000s, China experienced large-scale domestic infrastructure improvement, resulting in lower domestic trade and migration costs. How does such infrastructure improvement affect welfare and the skill premium in China? Do the impacts depend on production factor adjusments? In this section, we try to answer those questions. We consider a counterfactual economy in which China's domestic trade costs and migration costs are fixed at the initial level in 2000.

Table 9 summarizes the quantitative results. The results are generally consistent with previous analyses of uniform infrastructure improvement. Using the basic model, we find that the infrastructure improvement increases unskilled real wages by 1.6 percent and skilled wages by 1.8 percent. Allowing endogenous capital accumulation alone considerably enlarges welfare impacts: the welfare gains measured by unskilled and skilled wage changes increase to 2.9 and 4.4 percent respectively. Allowing upskilling in addition to capital accumulation further augments welfare impacts: the infrastructure shock increases unskilled and skilled wages now by 3.9 and 4.6 percent respectively. However, adding upskilling alone only generates limited welfare changes from the basic model simulation. Such different roles of upskilling with or without capital accumulation are evidence of the interaction effect between capital and skill accumulation.

Table 9 also shows that the infrastructure improvement impacts skill premium distinctly given different model assumptions. The basic model simulation suggests that the shock is slightly skill-biased, as it increases skill premium by 0.4 percent. The shock becomes strongly skill-biased given endogenous capital accumulation, with the shock raising skill premium by 1.4 percent. The reason is that the infrastructure improvement induces faster capital accumulation, increasing the return on skill. The shock then becomes unskill-biased under the simulation with skill acquisition but no capital accumulation. As infrastructure improvement increases the total skill ratio, the resulting larger supply of skills reduces the

Table 9: Aggregate Impacts of Infrastructure Improvement

	%Changes in Steady State						
	Capital	S.R.	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	2.49	0.15	3.49	4.82	1.29	4.14	4.61
With Upskilling	-	0.16	1.85	1.66	-0.22	1.18	3.22
With Capital	3.39	-	2.85	4.30	1.39	4.46	3.40
Basic Model	-	-	1.61	1.81	0.36	1.30	2.44

Notes: This table reports the steady state % changes of aggregate economic outcomes induced by China's infrastructure improvement in the early 2000s. From left to right economic outcomes are total capital stock, total skill ratio, real unskilled wage, real skilled wage, average skill premium, total GDP, and consumption equivalence. The "Full Model" is the baseline model; 'With Upskilling' refers to the model with skill acquisition but constant local capital stock; 'With Capital' refers to the model with endogenous capital accumulation but skill upgrading cost is infinite: $\kappa_s = \infty$; 'Basic Model' refers to the one with constant capital stock and $\kappa_s = \infty$. The real unskilled (skilled) wage is a weighted average with the weight of each city being the share of local unskilled (skilled) labor. GDP is the China's total output $\sum_{i=1}^{N-1} X_i^*$. C.E. is $100\% \times \Delta$ as defined before.

skill premium. A more interesting result here is that infrastructure improvement encourages skill upgrading. The main reason is that the infrastructure shock reduces geographic travel costs for both skill-type workers in the same absolute magnitude, but lowers skilled workers' migration friction relatively more since skilled workers face lower migration policy barriers than unskilled workers. In other words, the infrastructure improvement exaggerates unskilled workers' disadvantage in the discriminatory migration policy. Therefore, unskilled workers are more willing to transfer to skilled workers given the lower travel costs, resulting in a positive change in the total skill ratio. Finally, the infrastructure shock becomes skilled-biased again in the full model simulation as the positive effect from capital growth dominates the negative effect from a larger skill supply. But the skill supply adjustment still attenuates skill premium increases from 1.4 to 1.3 percent.

Lastly, we report the spatial dispersions of infrastructure improvement's impacts in table 10. Consistent with our main conclusion, capital accumulation generates highly heterogeneous spatial impacts on welfare but skill acquisition alone contributes little. The interaction between capital and skill accumulation further enlarges the spatial dispersion.

Table 10: Spatial Dispersion of Infrastructure Improvement's Impacts

	Standard Deviation of Changes in Steady State							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	22.71	1.18	13.75	4.16	5.11	2.10	1.31	2.39
With Upskilling	0.00	1.06	3.83	1.58	1.56	2.38	0.31	1.37
With Capital	18.95	2.37	10.76	3.90	4.02	1.83	1.24	2.17
Basic Model	0.00	1.25	4.05	1.21	1.51	1.80	0.28	0.89

	Max %Changes - Min %Changes in Steady State							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	158.46	8.02	85.79	26.90	35.68	13.01	7.37	17.51
With Upskilling	0.00	7.86	30.01	10.33	12.61	18.63	2.65	11.39
With Capital	128.22	13.78	78.48	24.84	27.54	11.18	7.14	15.91
Basic Model	0.00	9.99	29.51	8.71	12.62	17.76	2.45	7.57

Notes: This table reports the % changes of aggregate economic outcomes induced by China's infrastructure improvement in the early 2000s. From left to right economic outcomes are capital stock, skill ratio, real unskilled wage, real skilled wage, skill premium, GDP, and consumption equivalence. The "Full Model" is the baseline model; 'With Upskilling' refers to the model with skill acquisition but constant local capital stock; 'With Capital' refers to the model with endogenous capital accumulation but skill upgrading cost is infinite: $\kappa_s = \infty$; 'Basic Model' refers to the one with constant capital stock and $\kappa_s = \infty$. The real unskilled (skilled) wage is a weighted average with the weight of each city being the share of local unskilled (skilled) labor. GDP is the China's total output $\sum_{i=1}^{N-1} X_i^*$. C.E. is $100\% \times \Delta$ as defined before.

5 Conclusion

In this study, we develop a dynamic spatial framework to understand how economic shocks affect spatial factor accumulation and how the aggregate and spatial impacts depend on factor accumulation. The model features capital-skill complementarity, capital accumulation, and endogenous skill acquisition. Different skill types of workers are differentiated by their spatial mobilities and their roles in the production function. We then apply our framework to China's economy.

We find that physical and human capital accumulation interacts with each other in response to economic shocks, and the impacts of economic shocks crucially depend on the presence of factor accumulation. Ignoring both physical and human capital accumulation substantially underestimates the welfare impacts of shocks such as trade liberalization, infrastructure improvement, and productivity jump. A notable part of the downward bias is due to overlooking the interactive adjustments between capital accumulation and skill acquisition in response to the shock.

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Online Appendix

A Details of the Model

A.1 Price and Trade

Denote p_{it} as the price index at location i. By the nested preference structure and given the price of sector j's goods supplied by exporter n to i, $p^j_{in,t}$, the price index at i is

$$p_{it} = \prod_{j=1}^{J} \left(p^j_{it}\right)^{\gamma^j}, \tag{A.1}$$

where the sector-level price p^j_{it} is given by

$$p^j_{it} = \left[\sum_{n=1}^{N} \left(p^j_{in,t}\right)^{-\theta}\right]^{-\frac{1}{\theta}}. \tag{A.2}$$

The share of importer i's expenditure within industry j on goods supplied by exporter n is

$$\pi^j_{in,t} = \frac{(p^j_{in,t})^{-\theta}}{\sum_{m=1}^{N}(p^j_{im,t})^{-\theta}}. \tag{A.3}$$

A.2 Firm's Problem

In this part, we drop the time notation for brevity. The problem of a producer in sector j at location i is given by:

$$\min_{l,s,k} \; w^l_i l^j_i + w^h_i h^j_i + r_i k^j_i,$$

subject to:

$$z_i \left[(\mu^j)^{\frac{1}{\sigma}}(L^{ij}_i)^{\frac{\sigma-1}{\sigma}} + (1-\mu^j)^{\frac{1}{\sigma}}(L^{ej}_i)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \geq q^j_i \tag{A.4}$$

$$L^{ej}_i = \left[(\lambda^j)^{\frac{1}{\eta}}(k^j_i)^{\frac{\eta-1}{\eta}} + (1-\lambda^j)^{\frac{1}{\eta}}(L^{hj}_i)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}. \tag{A.5}$$

First order conditions for s_i^j and k_i^j yield:

$$k_i^j = \frac{\lambda_j}{1-\lambda_j}\left(\frac{w_i^s}{r_i}\right)^\eta L_i^{hj}. \tag{A.6}$$

Using this expression to replace k_i^j in equation (A.5) and define the price w_i^{ej} for composite input L_i^{ej} such that $w_i^{ej}L_i^{ej} = r_i k_i^j + w_i^h L_i^{hj}$, we obtain:

$$w_i^{ej} = \left[\lambda^j (r_{it})^{1-\eta} + (1-\lambda^j)(w_{it}^h)^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{A.7}$$

Similarly, first order conditions for L_i^{lj} and L_i^{hj} give:

$$L_i^{lj} = \frac{\mu_j}{1-\mu_j}\left(\frac{w_i^{ej}}{w_i^l}\right)^\sigma L_i^{hj}. \tag{A.8}$$

Using equation (A.8) and define the unit cost c_i^j for the variety q_i^j such that $c_i^j q_i^j = w_i^l L_i^{lj} + w_i^{ej} L_i^{ej}$, we obtain:

$$c_i^j = \frac{1}{z_i}\left[\mu^j (w_i^l)^{1-\sigma} + (1-\mu^j)(w_i^e)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{A.9}$$

A.3 Numerical Algorithm for Solving Steady State

We first write down the corresponding equilibrium conditions in the steady state. The value function (1)(2)(5) become:

$$v_i^{l*} = \ln b_i + \ln \frac{w_i^{l*}}{p_i^*} + \psi \ln\left[\exp\left(\tilde{v}_i^{l*}/\psi\right) + \exp\left(\tilde{v}_i^{s*}/\psi\right)\right] \tag{A.10}$$

$$\text{with } \tilde{v}_i^{d*} = \rho \ln \sum_{g=1}^{N} \exp\left[(\xi\beta v_g^{d*} - \kappa_{gi}^{d*})/\rho\right], \; d = l, s.$$

$$v_i^{s*} = \ln b_i + \ln \frac{\iota w_{i*}^l}{p_i^*} - \kappa_s + \rho \ln \sum_{g=1}^{N} \exp\left[(\xi\beta v_g^{h*} - \kappa_{gi}^h)/\rho\right], \tag{A.11}$$

$$v_i^{h*} = \ln b_i + \ln \frac{w_i^{h*}}{p_i^*} + \rho \ln \sum_{g=1}^{N} \exp\left[(\xi \beta v_g^{h*} - \kappa_{gi}^{h})/\rho\right], \tag{A.12}$$

the skill upgrading matrix (3) and migration matrix (4) become

$$D_i^{ls*} = \frac{\exp\left[(v_i^{s*})/\psi\right]}{\exp\left[(v_i^{l*})/\psi\right] + \exp\left[(v_i^{s*})/\psi\right]}, \tag{A.13}$$

$$D_{in}^{d*} = \frac{\exp\left[(\xi \beta v_i^{d*} - \kappa_{in}^{d*})/\rho\right]}{\sum_{g=1}^{N} \exp\left[(\xi \beta v_g^{d*} - \kappa_{gn}^{d*})/\rho\right]}, \; d = l, s, h \tag{A.14}$$

and the labor supply (6) - (8) become

$$L_i^{l*} = \xi \sum_{n=1}^{N} D_{in}^{l*} \left(L_n^{l*} - D_n^{ls*} L_n^{l*}\right) + \left(L_i^{l*} + L_i^{s*} + L_i^{h*}\right)(1 - \xi), \tag{A.15}$$

$$L_i^{s*} = \xi \sum_{n=1}^{N} D_{in}^{s*} D_n^{ls*} L_n^{l*}, \tag{A.16}$$

$$L_i^{h*} = \xi \left(\sum_{n=1}^{N} D_{in}^{h*} \left(L_n^{h*} + L_n^{s*}\right) \right). \tag{A.17}$$

The market clearing conditions (16)(17)(18)(19) become:

$$X_i^{j*} = \sum_{n=1}^{N} S_{ni}^{j*} \left[\gamma_j \sum_{m=1}^{J} X_n^{m*} \right], \tag{A.18}$$

$$w_i^{l*} = \frac{\sum_{j=1}^{J} \phi_i^{lj*} X_i^{j*}}{\tilde{L}_i^{l*}} \tag{A.19}$$

$$w_i^{h*} = \frac{\sum_{j=1}^{J} \phi_i^{hj*} X_i^{j*}}{L_i^{h*}} \tag{A.20}$$

$$r_i^{*} = \frac{\sum_{j=1}^{J} \phi_i^{kj*} X_i^{j*}}{k_i^{*}}, \tag{A.21}$$

with steady-state factor income shares given by:

$$\phi_i^{lj*} = \left[1 + \frac{1-\mu^j}{\mu^j} (\frac{w_i^{l*}}{w_i^{e*}})^{\sigma-1}\right]^{-1} \tag{A.22}$$

$$\phi_i^{hj*} = \left[1 + \frac{\mu^j}{1-\mu^j} (\frac{w_i^{e*}}{w_i^{l*}})^{\sigma-1}\right]^{-1} \left[1 + \frac{\lambda^j}{1-\lambda^j} (\frac{w_i^{h*}}{r_i^{*}})^{\eta-1}\right]^{-1} \tag{A.23}$$

$$\phi_i^{kj*} = \left[1 + \frac{\mu^j}{1-\mu^j} (\frac{w_i^{e*}}{w_i^{l*}})^{\sigma-1}\right]^{-1} \left[1 + \frac{1-\lambda^j}{\lambda^j} (\frac{r_i^{*}}{w_i^{h*}})^{\eta-1}\right]^{-1}. \tag{A.24}$$

The trade share adopts the following expression:

$$S_{ni}^{j*} = \frac{(p_{ni}^{j*})^{-\theta}}{\sum_{g=1}^{N} (p_{nm}^{j*})^{-\theta}}, \tag{A.25}$$

where

$$p_{ni}^{j*} = \frac{\tau_{ni}}{z_i^{*}} \left[\mu^j (w_i^{l*})^{1-\sigma} + (1-\mu^j) \left[\lambda^j (r_i^{*})^{1-\eta} + (1-\lambda^j)(w_i^{h*})^{1-\eta}\right]^{\frac{1-\sigma}{1-\eta}}\right]^{\frac{1}{1-\sigma}}.$$

The capital accumulation condition becomes:

$$k_i^{*} = \xi\beta(1-\delta+\frac{r_i^{*}}{p_i^{*}})k_i^{*}, \text{ with } p_i^{*} = \prod_{j=1}^{J}\left[\sum_{n=1}^{N}(p_{in}^{j*})^{-\theta}\right]^{-\frac{\gamma_j}{\theta}}. \tag{A.26}$$

Given these conditions, the algorithm is as follows.

(1) Start with an initial guess of value functions $\{v_i^{l(0)}, v_i^{s(0)}, v_i^{h(0)}\}_{i=1}^{N}$ and factor allocations $\{L_i^{l(0)}, L_i^{s(0)}, L_i^{h(0)}, k_i^{(0)}\}_{i=1}^{N}$.

(2) Given $\{v_i^{l(0)}, v_i^{s(0)}, v_i^{h(0)}\}_{i=1}^N$, compute skill upgrading probability $\{D_i^{ls}\}_{i=1}^N$ and migration shares $\{D_{ig}^{ed}\}_{i=1}^N$ by (A.13) and (A.14), and then solve new labor allocations by (A.15), (A.16) and (A.17) to obtain $\{L_i^{l(1)}, L_i^{s(1)}, L_i^{h(1)}\}_{i=1}^N$. The total local unskilled labor supply is obtained as $\tilde{L}_i^{l(1)} = L_i^{l(1)}(1 - D_i^{ls}) + \iota L_i^{s(1)}$

(3) Given $\{\tilde{L}_i^{l(1)}, L_i^{h(1)}, k_i^{(0)}\}_{i=1}^N$, solve factor prices $\{w_i^l, w_i^h, r_i\}_{i=1}^N$ from markets clearing conditions as follows:

- (a) set an initial guess of factor prices $\{w_i^l, w_i^h, r_i\}_{i=1}^N$,
- (b) compute factor incomes shares $\{\phi_i^{lj}, \phi_i^{hj}, \phi_i^{kj}\}_{i=1}^N$ from (A.22), (A.23), (A.24),
- (c) compute prices $\{p_{ni}\}_{n=1,i=1}^{N,N}$ and trade shares $\{S_{ni}\}_{i=1,n=1}^{N,N}$ from (A.25),
- (d) solve total output X_i^{j*} by (A.18)
- (e) obtain new factor prices $\{w_i^l, w_i^h, r_i\}_{i=1}^N$ by (A.19), (A.20), (A.21),
- (f) iterate until factor prices converge.

(4) Use $\{w_i^l, w_i^h, r_i\}_{i=1}^N$ to compute price index $\{p_i\}_{i=1}^N$ and solve new captial $\{k_i^{(1)}\}_{i=1}^N$ by (A.26). (5) Given $\{v_i^{l(0)}, v_i^{s(0)}, v_i^{h(0)}, w_i^{l(1)}, w_i^{h(1)}, p_i\}_{i=1}^N$, solve new value functions $\{v_i^{l(1)}, v_i^{s(1)}, v_i^{h(1)}\}_{i=1}^N$ by (A.10) - (A.12). (6) Update $\{v_i^{l(0)}, v_i^{s(0)}, v_i^{h(0)}, L_i^{l(0)}, L_i^{s(0)}, L_i^{h(0)}, k_i^{(0)}\}_{i=1}^N$ from $\{v_i^{l(1)}, v_i^{s(1)}, L_i^{l(1)}, L_i^{s(1)}, L_i^{h(1)}, k$
(7) Repeat steps (2)-(6) until value functions $\{v_i^l, v_i^s, v_i^h\}_{i=1}^N$ converge.

A.4 Numerical Algorithm for Solving Path Equilibrium

Given the initial allocations of labor and capital, $\{L_{i0}^l, L_{i0}^s, L_{i0}^h, k_{i0}\}$, we solve a transition path of length T towards a steady state using a shooting algorithm as follows.

(1) Start with an initial guess of value functions and capital stocks $\{v_{it}^{l(0)}, v_{it}^{s(0)}, v_{it}^{h(0)}\}_{i=1,t=1}^{N,T}$, where $v_{iT}^{l(0)}$, $v_{iT}^{s(0)}$ and $v_{iT}^{h(0)}$ are approximated by steady-state level of value functions.

(2) Given $\{v_{it}^{l(0)}, v_{it}^{s(0)}, v_{it}^{h(0)}\}_{i=1,t=1}^{N,T}$, solve upskilling probability $\{D_{it}^{ls}\}_{i=1,t=1}^{N,T}$ and migration shares $\{D_{in,t}\}_{i=1,t=1}^{N,T}$ from (3) and (4).

(3) Use $\{D_{it}^{ls}, D_{in,t}\}_{i=1,t=1}^{N,T}$ and $\{L_{i0}^l, L_{i0}^s, L_{i0}^h\}$ to solve $\{L_{it}^l, L_{it}^s, L_{it}^h\}_{i=1,t=1}^{N,T}$ by (6) - (8). Then compute total local unskilled labor supply as $\tilde{L}_{it}^l = L_{it}^l(1 - D_{it}^{ls}) + \iota L_{it}^s$.

(4) For each time period t, use current state variables $\{\tilde{L}^l_{it}, L^h_{it}, k^{(0)}_{it}\}_{i=1}^N$ to solve factor prices $\{w^l_{it}, w^h_{it}, r_{it}\}_{i=1}^N$:

- (a) set an initial guess of factor prices $\{w^l_{it}, w^h_{it}, r_{it}\}_{i=1}^N$,
- (b) compute factor incomes shares $\{\phi^{lj}_{it}, \phi^{hj}_{it}, \phi^{kj}_{it}\}_{i=1}^N$ from (12), (13), (14),
- (c) compute trade shares $\{S^j_{ni,t}\}_{i=1}^N$ from (15) and (A.3),
- (d) solve total output by (19),
- (e) solve new factor prices by (16), (17), (18),
- (f) iterate until factor prices converge.

(5) Use solved factor prices $\{w^l_{it}, w^h_{it}, r_{it}\}_{i=1,t=1}^{N,T}$ to compute $\{p_{ni,t}\}_{i=1,t=1}^{N,T}$ by (15). Then obtain price index $\{p_{nt}\}_{n=1,t=1}^{N,T}$ by (A.2) and solve new captial allocations sequence $\{k^{(1)}_i\}_{i=1,t=1}^{N,T}$ from k_{i0} and (9).

(6) Set $\{v^{l(1)}_{iT}, v^{s(1)}_{iT}, v^{h(1)}_{iT}\} = \{v^{l(0)}_{iT}, v^{s(0)}_{iT}, v^{h(0)}_{iT}\}$. Given $\{w^l_{it}, w^h_{it}, p_i\}_{i=1,t=1}^{N,T}$ and $\{v^{l(1)}_{iT}, v^{s(1)}_{iT}, v^{h(1)}_{iT}\}$, solve new value functions $\{v^{l(1)}_{it}, v^{s(1)}_{it}, v^{h(1)}_{it}\}_{i=1,t=1}^{N,T-1}$ backward by (1), (2) and (5).

(7) Update $\{v^{l(0)}_{it}, v^{s(0)}_{it}, v^{h(0)}_{it}\}_{i=1,t=1}^{N,T}$ from $\{v^{l(1)}_{it}, v^{s(1)}_{it}, v^{h(1)}_{it}\}_{i=1,t=1}^{N,T}$.

(8) Repeat steps (2)-(7) until value functions $\{v^l_{it}, v^s_{it}, v^h_{it}\}_{i=1,t=1}^{N,T}$ converge.

B Details of Data and Quantification

B.1 Data Sources for China

1. The **2000 Census** and **2010 Census** in China. These datasets provide prefecture-level population and skill ratios in the years 2000 and 2010. We aggregate the 2010 skill ratios at the country level, which is then used to identify the skill upgrading cost.

2. The **China's 2002 Industrial Classification for National Economic Activities** (GB/T 4754-2002) provides a detailed classification of 96 industries at a two-digit level. We exclude industries in agriculture and mining and the waste processing industry, resulting in a total number of 82 industries.

3. The **One Percent Population Survey** in 2005. We use this dataset to obtain prefecture-level bilateral migrant flows in 2005, the industry-level ratio of total skilled workers' income to total workers' income for 96 industries (industrial skill intensities), and prefecture-level skill premiums in 2005.

4. The **City Statistical Yearbooks** of China, from which we obtain prefecture-level GDP in 2000 and 2010, gross fixed capital formation from 1994 to 2000, and yearly investment price index for 1994-2000. We use these data on investment to construct prefecture-level capital stocks and then prefectural capital shares in 2000.

5. The **2002 China Input-Output Table**. The IO Table provides final consumption and capital income shares in the value-added for 42 industries at the two-digit level. We excluded agricultural and mining industries and manually mapped the remaining 37 industries with the 82 industries in the GB/T 4754-2002 classification so that the industry classification is consistent.

B.2 Data Sources for the Rest of the World (ROW)

1. The **OECD Statistics**. This database provides the initial population aged from 25 to 64 in the year 2000 for 33 countries, including China. We combine the total population from this source and the prefecture population share in the 2000 census to compute the prefectural population in the initial state. We aggregate the remaining countries' populations as the population of the ROW. We also observe country-level shares of unskilled workers from the same database out of the total workers. We obtain the initial skill ratio of the ROW as the ratio of the ROW's total skilled workers to its total workers.

2. The **Penn World Table**. We use PWT version 10.0 to obtain initial capital stocks in the year 2000 for countries in the ROW and China. Each country's capital stock is in units of 2000 USD, where we use the exchange rate for the year 2000 from the National Account data in the same database. The initial capital stock of the ROW is computed as an aggregate of the capital stocks of all 32 countries in the list. We infer

the prefectural-level capital stock by combining the total capital stock from PWT and the prefectural capital shares calculated from the City Statistical Yearbooks of China.

3. The **World Input-Output Database (WIOD)**. We use the WIOD 2016 Release to obtain China's sectoral trade-to-GDP ratios from 2000 to 2006. The World Input-Output Tables provide intercountry trade flows for 56 industries, including 19 manufacturing industries. China's national IO tables from 2000 to 2006 provide China's sectoral value added.

4. The **IPUMS USA**. We use the one-percent sample of the U.S. 2000 Census from IPUMS USA to infer the skilled workers' income share in each sector. We match China's 42 industries with the NAICS 2007 code to ensure consistent sector classification. We define skilled workers as workers with an education level of 12 grade or above, i.e., high school graduates or college graduates.

5. The **2007 Benchmark Input-Output Acount** of the U.S. provides capital and labor income share in the total value added at the 6-digit industry level. Again, we match China's 42 industries with the NAICS 2007 code. The labor income share is then divided between skilled and unskilled workers using the results from IPUMS USA.

B.3 Additional Tables

Table B.1: List of Countries in the ROW

Australia	Belgium	Canada	Costa Rica	Czech Republic
Denmark	Estonia	Finland	France	Germany
Greece	Hungary	Ireland	Italy	Japan
Korea	Latvia	Lithuania	Luxembourg	Mexico
Netherlands	New Zealand	Poland	Portugal	Slovak Republic
Slovenia	Spain	Sweden	Switzerland	Türkiye
United Kingdom	United States			

Notes: This table lists 32 OECD countries that are selected as the ROW because of their data availability.

Table B.2: List of Port Cities

Tianjin	Tangshan	Qinhuangdao	Dalian	Dandong	Jinzhou	Shanghai
Suzhou	Nantong	Ningbo	Wenzhou	Jiaxing	Fuzhou	Xiamen
Quanzhou	Qingdao	Yantai	Weihai	Guangzhou	Shenzhen	Zhuhai
Shantou	Foshan	Jiangmen	Zhanjiang	Huizhou	Haikou	

Notes: This table lists the 27 prefectures that 1) import and export from the international markets in the Chinese Customs database and 2) are on the coast

B.4 Sector Classification

We classify the 82 industries from GB/T 4754-2002 Chinese Classification (GB hereafter) into four sectors based on skill intensities: skilled manufacturing sector, unskilled manufacturing sector, skilled service sector, and unskilled service sector. Specifically, we compute the skill intensity of each industry by taking the ratio of skilled workers' income to total labor income for each industry. Then, we rank manufacturing and service industries separately by skill intensity. We treat industries above the median skill intensity as the *skilled-intensive industries* and group them to define the skilled sector. Those below the median skill intensity are aggregated as unskilled-intensive sectors. The skill intensities of each industry are estimated using the *One Percent Population Survey.* Table B.3 and B.4 show the corresponding result.

To obtain sector-level capital and labor income share, we utilize the 2002 China Input-Output Table and match its 37 industries with 82 GB industries. Usually, the 2002 IO table industries each contain multiple GB industries. Since we define skilled sectors based on the GB system, if all GB industries within one IO table industry are classified as skilled industries, then the IO table industry is also considered skilled. For one IO table industry containing both skilled and unskilled GB industries, we consider the whole industry as a skilled one if there are more skilled GB industries within it than unskilled GB industries. Then, we aggregate IO Table industries into four sectors by skill intensity and compute the corresponding sectoral capital income shares as the total sectoral capital income ratio to sectoral value added.

Next, we use the WIOD World Input-Output table to obtain China's sector-level trade-to-GDP ratios. We only consider trade in the manufacturing sector and trade flows between

China and 32 countries included in the ROW. To obtain sectoral imports and exports of China, we manually map the 19 manufacturing industries in the WIOD with 16 Chinese manufacturing industries in GB 42 industry classifications and define the skilled and unskilled sectors. From the WIOD, we also use China's national IO tables from 2000 to 2006 to obtain China's sectoral value added. Given imports and exports data and the value added, we compute China's sectoral import/export-to-GDP ratio between 2000 and 2006 by taking the ratio of import/export to value added.

Lastly, we use the U.S. sectoral income shares to represent those of the ROW. we manually match China's 42 IO table industries with the NAICS 2007 code. Table B.3 and B.4 show matching results. Then, we aggregate those industries into four sectors as before and compute skilled workers' income share as the ratio of total skilled workers' income to total workers' income for each sector.

Table B.3: Manufacturing Sectors

Panel A: Unskilled Manufacturing				Panel B: Skilled Manufacturing			
IO	Description	GB 2002	NACIS	IO	Description	GB 2002	NACIS
06	Food&Tabacco	C13-16	311-312	11	Petroleum	C25	324
07	Textile	C17	313	12	Chemicals	C26-30	325-326
08	Clothing	C18-19	314-316	14	Primary metals	C32-33	327
09	Wood&Furniture	C20-21	321,337	16	Machinery	C35-36	333
10	Paper&Printing	C22-24	322-323	17	Transportation equipment	C37	336
13	Nonmetallic mineral products	C31	327	18	Electrical equipment	C39	335
15	Manufactures of metal	C34	332	19	Telecommunication equipment	C40	334
21	Other manufactures	C42	339	20	Instruments	C41	334

Notes: This table shows the composition of the skilled and unskilled manufacturing sectors. Column "IO" shows the industry number in the 2002 China Input-Output table; "GB 2002" is from the industry classification system of China's 2002 Industrial Classification for National Economic Activities; "NACIS" refers to the NACIS 2007 code. Both "GB 2002" and "NACIS" are manually matched with the IO industry by description.

B.5 Estimate Migration Costs

We provide the details on estimating the migration costs here from the *One Percent Population Survey* in 2005. The survey records the individual's current location and asks for the location one year and five years ago. In addition to the location history, we also observe the place of hukou registration.

Table B.4: Service Sectors

Panel A: Unskilled Service				Panel B: Skilled Service			
IO	Description	GB 2002	NACIS	IO	Description	GB 2002	NACIS
24	Natural gas	D45	2212	23	Electric power	D44	2211
25	Water	D46	2213	29	Computer service	G60-62	513-514
26	Construction	E47-50	23	32	Finance	J68-71	521-525
27	Transportation	F51-58	481-487,493	33	Real estate	K72	531
28	Postal	F59	491	34	Rental&Business	L73-74	532-561
30	Wholesale&Retail	H63,H65	42,441,445,452	36	Scientific service	M75	5412
31	Accommodation&Food	I66-67	721-722	37	Technical services	M76-N79	5412
38	Other services	N81-O83	81	39	Education	P84	61
				40	Health&Welfare	Q85-87	622-624
				41	Culture, Sports & Entertainment	R88-92	511-512,711-713
				42	Government	S93-97	G

Notes: This table shows the composition of the skilled and unskilled manufacturing sectors. Column "IO" shows the industry number in the 2002 China Input-Output table; "GB 2002" is from the industry classification system of China's 2002 Industrial Classification for National Economic Activities; "NACIS" refers to the NACIS 2007 code. Both "GB 2002" and "NACIS" are manually matched with the IO industry by description.

We first note that the stock of migrants from location i to location g consists of current and past movers from i that choose to stay in g. To be specific, the ratio of migrant stock in location g with origin i to the origin city's stock of workers at time t can be expressed as

$$\bar{D}^d_{gi,t} = \frac{L^d_{it} D^d_{gi,t} + \sum_{\tau=1}^{\infty} L^d_{it-\tau} D^d_{gi,t-\tau} (D^d_{gg,t-\tau})^\tau}{L^d_{it}}, \; d = l, s. \tag{B.1}$$

In the numerator on the right-hand side, the first term is migration flow from the origin i at period t, where $D^d_{gi,t}$ is the migration probability, and L^d_{it} is the population at the origin i. In addition to the most recent movers, the current stock of migrants from location i also includes those who moved τ periods ago $L^d_{it-\tau} D^d_{gi,t-\tau}$ and choose to stay in location g thereafter with a probability $(D^d_{gg,t-\tau})^\tau$. The second term in the numerator counts these migrants retrospectively from $\tau = 1$ to distance history.

Assume that the migrant stocks are observed at a steady state so that $D^d_{gi,t} = D^d_{gi}$, then this ratio can be simplified as:

$$\bar{D}^d_{gi} = \frac{D^d_{gi}}{1 - D^d_{gg}}, \tag{B.2}$$

where D^d_{gi} is defined in the model as

$$D^d_{gi} = \frac{\exp\left[(\beta v^d_g - \kappa^d_{gi})/\rho\right]}{\sum_{n=1}^{N} \exp\left[(\beta v^d_n - \kappa^d_{ni})/\rho\right]}. \tag{B.3}$$

Therefore, double differencing the migrant stock share yields our main structural equation that can be used to estimate the migration costs:

$$\frac{\bar{D}^d_{gi}}{\bar{D}^d_{ii}}\frac{\bar{D}^d_{ig}}{\bar{D}^d_{gg}} = \frac{D^d_{gi}}{D^d_{ii}}\frac{D^d_{ig}}{D^d_{gg}} = \exp\left[-\frac{1}{\rho}(\kappa^d_{gi} + \kappa^d_{ig})\right], \tag{B.4}$$

where we use the result

$$\frac{D^d_{gi}}{D^d_{ii}} = \frac{\exp\left[(\beta v^d_g - \kappa^d_{gi})/\rho\right]}{\exp\left[(\beta v^d_i)/\rho\right]} = \exp\left\{\left[\beta\left(v^d_g - v^d_i\right) - \kappa_{gi}\right]/\rho\right\}. \tag{B.5}$$

C Additional Quantitative Results

C.1 Short-run Impacts of Trade and Infrastructure Shocks

Table C.1: Short-run Aggregate Impacts of Trade Liberalization

	%Changes in 2010						
	Capital	S.R.	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	0.91	-0.12	2.75	1.39	-1.33	2.30	3.13
With Upskilling	-	-0.15	2.16	0.73	-1.39	1.41	1.61
With Capital	0.89	-	2.81	1.32	-1.45	2.32	3.44
Basic Model	-	-	2.26	0.61	-1.60	1.44	2.29

Notes: This table reports the short-run % changes of aggregate economic outcomes in China induced by a uniform infrastructure shock under different model specifications.

C.2 Spatial Impacts of Trade and Infrastructure Shocks in Steady State

Table C.2: Spatial Dispersion of Trade Liberalization's Impacts

	Standard Deviation of Changes in 2010							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	0.35	0.08	0.19	0.67	0.61	0.19	0.85	0.56
With Upskilling	0.00	0.05	0.13	0.60	0.45	0.20	0.62	0.35
With Capital	0.35	0.12	0.20	0.66	0.61	0.22	0.85	0.53
Basic Model	0.00	0.08	0.15	0.60	0.45	0.23	0.63	0.40

	Max %Changes - Min %Changes in 2010							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	1.64	0.54	1.46	3.17	3.05	1.14	4.04	3.07
With Upskilling	0.00	0.57	1.10	3.04	2.23	1.34	3.18	1.98
With Capital	1.63	0.84	1.46	3.19	3.20	1.28	4.07	2.75
Basic Model	0.00	0.86	1.27	3.11	2.33	1.39	3.22	2.52

Notes: This table reports the spatial dispersion of % changes of local economic outcomes in China induced by liberalization under different model specifications.

Table C.3: Short-run Aggregate Impacts of Infrastructure Improvement

	%Changes in 2010						
	Capital	S.R.	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	0.37	0.12	1.66	1.57	-0.05	1.33	5.55
With Upskilling	-	0.08	1.54	1.41	-0.09	1.30	4.21
With Capital	0.40	-	1.56	1.66	0.18	1.38	4.36
Basic Model	-	-	1.47	1.46	0.09	1.32	3.71

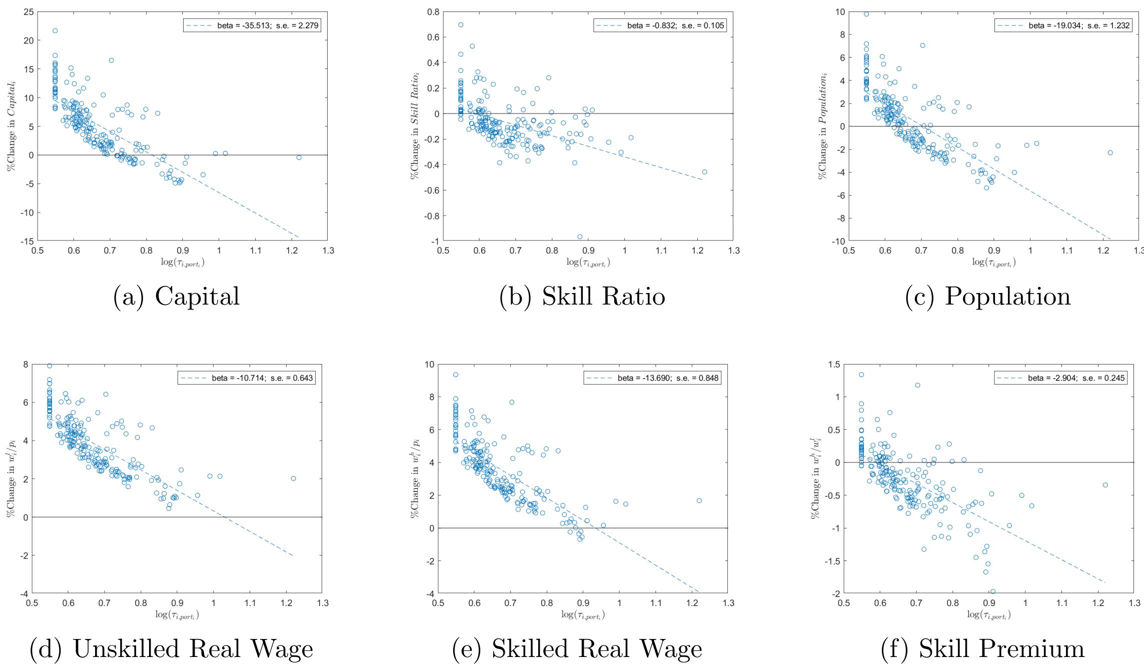
Notes: This table reports the short-run % changes of aggregate economic outcomes in China induced by infrastructure shock under different model specifications.

Table C.4: Spatial Dispersion of Infrastructure Improvement's Impacts

	Standard Deviation of Changes in 2010							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	0.52	0.57	1.31	1.40	1.15	0.89	2.08	3.30
With Upskilling	0.00	0.48	1.12	1.27	1.01	0.84	1.69	2.73
With Capital	0.54	0.66	1.39	1.39	1.15	0.92	2.14	3.18
Basic Model	0.00	0.56	1.20	1.26	1.02	0.86	1.75	2.79

	Max %Changes - Min %Changes in 2010							
	Capital	S.R.	Pop	w^l/p	w^h/p	S.P.	GDP	C.E.
Full Model	4.54	4.51	10.24	10.09	9.24	6.61	14.05	19.20
With Upskilling	0.00	4.07	9.43	9.04	7.27	6.52	11.33	16.21
With Capital	4.63	5.22	10.75	9.97	9.49	6.71	14.65	18.56
Basic Model	0.00	4.85	9.70	9.06	7.43	6.70	11.84	16.45

Notes: This table reports the spatial dispersion of % changes of local economic outcomes in China induced by infrastructure improvement under different model specifications.

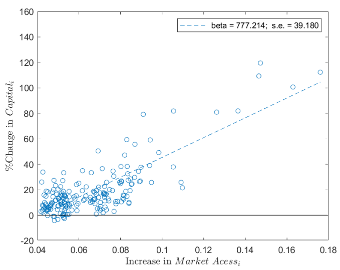


(a) Capital (b) Skill Ratio (c) Population

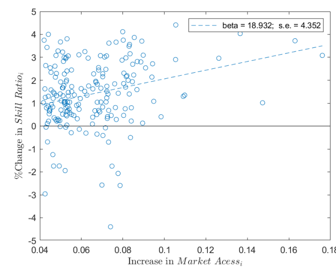
(d) Unskilled Real Wage (e) Skilled Real Wage (f) Skill Premium

Figure C.1: Spatial Impacts of Trade Liberalization in Steady States

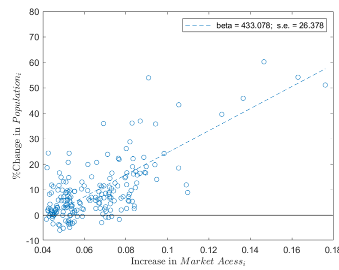
Notes: these figures show the spatial impacts of China's accession to WTO on production factors, real wages, and skill premiums across Chinese prefectures in steady states. The results come from the full model simulation. The horizontal axis measures each city's distance to the ROW. Each dot represents a prefecture-level city. The straight lines are linear fits.



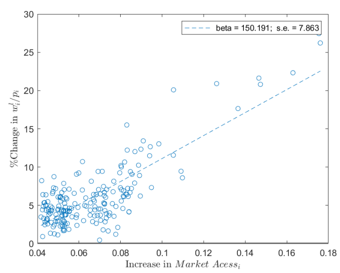
(a) Capital



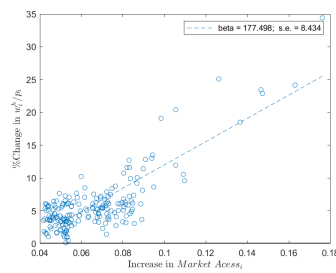
(b) Skill Ratio



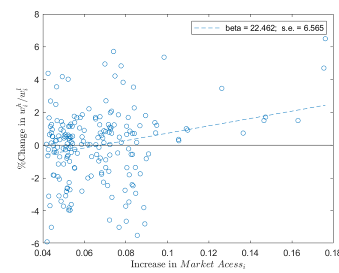
(c) Population



(d) Unskilled Real Wage



(e) Skilled Real Wage



(f) Skill Premium

Figure C.2: Spatial Impacts of Infrastructure Improvement in Steady States

Notes: these figures show the spatial impacts of infrastructure improvement in China during 2000-2015 on production factors, real wages, and skill premiums across Chinese prefectures in steady states. The results come from the full model simulation. The horizontal axis measures each city's increase in market access due to infrastructure improvement. Each dot represents a prefecture-level city. The straight lines are linear fits.