Export Expansion, Skill Acquisition and Industry Specialization: Evidence from China*

Bingjing Li†

November 2015

Abstract

Have the decline in trade barriers and the resulting export expansion affected human capital accumulation in China in the past two decades? To answer this question, I develop a trade model with endogenous skill formation and use it to analyze the impact of export expansion on school enrollment in China during the period 1990 to 2005. Following a theoretically consistent approach, I exploit the variation in regional exposures to high- and low-skill export demand shocks, which stem from the diverse initial industry composition across regions, and differential skill intensities across industries. The empirical analysis shows that high-skill export shocks raise both high school and college enrollments, while low-skill export shocks depress both. The amplified differences in skill abundance across regions reinforce the initial industry specialization pattern. These findings suggest a mutually reinforcing relationship between regional comparative advantage and skill formation. The counterfactual analysis shows that the integration into the world market over the past decades lowered the educational attainment for most regions in China, due to their initial comparative advantage in low-skill industries. In addition, further trade liberalization will accelerate the regional divergence in educational attainment and industry specialization.

*I am grateful to Matilde Bombardini, David Green and Tomasz Swiecki for their continued guidance and encouragement. I also thank the seminar participants at the VSE empirical lunch and macro lunch for the comments and suggestions. All errors are on my own.

†Vancouver School of Economics, University of British Columbia; Email: bingjing.crystal@gmail.com

1 Introduction

The impact of "Made in China" on labor markets has been studied extensively in recent years. Pierce and Schott (2012), Ebenstein et al. (2012), Autor, Dorn and Hanson (2013), Autor et al. (2014), Utar (2014) and Balsvik, Jensen and Salvanes (2015) find that the manufacturing sector in developed countries suffered because of import competition from China. However, little is known about the flip side of the coin, i.e., the consequences of China's export expansion on its own labor market.[1] Drawing on a rich data set on sub-national economies, the present paper examines the differential impact of export expansion on local markets within China between 1990 and 2005. The paper has two focuses. First, it analyzes the effects of export demand shocks on human capital accumulation or decumulation in local economies, by exploiting cross-market variation in export exposure stemming from initial differences in industrial specialization. Second, it investigates the dynamics of regional industrial specialization resulting from the trade-induced shifts in skill supply.

Understanding the linkages among trade, regional comparative advantage and human capital accumulation is important. In recent decades, export-oriented policies have been associated with industrialization and economic growth in many developing countries. Nevertheless, there are few studies inquiring the long term effects of these export-led growth strategies. In particular, as is suggested by Findlay and Kierzkowski (1983), trade may exacerbate economic differences across countries through its effect on educational attainment, which is thought to be a key ingredient for sustained economic development.

China provides an interesting setting in which to study the relations. Over the period spanned by the main data (1990-2005), China experienced two waves of trade liberalization. The first took place in 1992, when Deng Xiaoping made his famous southern tour to Guangdong province and reasserted the economic reforming and opening agenda. Favorable trade policies were adopted from that time and greatly boosted exports. Exports quadrupled in the 1990s, from 62 billion USD in 1990 to 248 billion USD in 2000. Accession to the WTO in 2001 further accelerated export expansion. Total exports tripled from 2000 to 2005, from 248 billion to 759 billion USD.

[1] To the best of my knowledge, Han, Liu and Zhang (2012) is the only paper studying the differential effects of trade liberalization on different regions within China. Employing the geographic distance to the coast as a proxy for export exposure, they find that China's accession to the WTO is significantly associated with rising wage inequality and skill premium in high-exposure regions.

In the meantime, there was a substantial reduction in export barriers. The effective export tariff decreased from 8.4% in 1990 to 3.5% in 2005. Several features of China's economy make the analysis and identification in this study feasible. The country's large geographic diversity is associated with considerable variation in skill endowment and industry composition across regions. Moreover, the household registration system greatly restricts the inter-region migration (Tombe and Zhu, 2014). Because of such labor market frictions, China's micro regions are effectively like local labor markets, which allows me to conduct the analysis at the sub-national level.

I extend a two-factor, multiple-sector and multiple-region Eaton and Kortum (2002) model by endogenizing skill formation. In the framework, each agent is endowed with two-dimensional productivities, which represent the aptitude at being an educated or uneducated worker. Based on labor market conditions, agents sort themselves into schools. From the model, I derive a simple reduced form equation linking changes in school enrollment to exogenous export demand shocks that differentially affect the education decision. The causal effect of export expansion on skill acquisition is carefully studied using an empirical approach guided by the model. Specifically, during a given period regions experience different low-skill and high-skill export demand shocks, which stem from the diverse initial industry composition across regions and the various skill intensities of different industries. The shocks alter the skill premium in local markets and hence the incentives to acquire education.

To construct the regional low- and high-skill export shocks in a theoretically consistent way, I proceed as follows. First, to isolate the external export demand shocks from other factors that may also be associated with export growth, such as productivity and labor supply, I only employ the component of exports that is predicted by the change in tariffs faced by Chinese exporters over time in different sectors. Second, the predicted export expansion is allocated to various regions according to initial sectoral employment shares. Finally, the apportioned exports are attributed to high skilled (low skilled) labor according to sectoral skill intensities and divided by the total amount of high skilled (low skilled) workers. The high-skill (low-skill) export shock can therefore be interpreted as export exposure in dollars per skilled (unskilled) worker.

Next, school enrollments of young people aged 16 to 22 across China's prefectures are related to the regional export shocks at different skill levels during the period 1990 to 2005. A 1000 USD low-skill export shock is estimated to reduce high-school enrollment rate by 3.1 percentage points and college enrollment rate by 2.4 percentage points. Conversely, a 1000 USD high-skill export shock raises the high-school enrollment rate by 0.8 percentage point and college enrollment rate by 1 percentage point. I address a series of issues that may contaminate these results, including non-local export expansions, import shocks, and selective migration, among others. None of these potential confounding factors affects the robustness of the findings.

To study whether the enlarged differences in skill abundance reinforce regional industry specialization, I link the change in industry employment share from 2000 to 2010 to the changes in school enrollment rate between 1990 and 2000, and instrument the latter with the export demand shocks. An increase in college enrollment is found to reduce the employment share of low-skill industries and raise the employment share of high-skill industries in the subsequent decade. The 2SLS estimates suggest that a 10 percentage point rise in college enrollment rate during the 1990s increases the employment share of a high-skill industry by 0.87 percentage point, while lowers the employment share of a low-skill industry by 0.78 percentage point in the 2000s.

These empirical findings suggest a mutually reinforcing relationship between regional comparative advantage and skill formation. Due to nationwide trade liberalization, regions that initially specialized in low-skill industries received relatively larger low-skill export shocks, which deskilled the local labor force. The change in skill supply strengthened their initial comparative advantage. As a result, these regions became more specialized in the low-skill sector in the subsequent period, making them more prone to low-skill export shocks in the future. The converse will be the case for a region initially specialized in high-skill industries.

To assess the general equilibrium effects of trade liberalization on human capital accumulation in China, I calibrate the model to bilateral trade flows and China's micro-level data and evaluate the implications of past and future trade liberalization for China. The counterfactual analysis finds that trade liberalization in past decades lowered educational attainment for most regions in China. In addition, further globalization will lead to further regional divergence in educational attainment and industry specialization. A 30 percent reduction in external trade cost is found to reduce the school enrollment in North Coast (the most negatively affected region) by 8 percents and increase the school enrollment in North Municipality (the most positively affected region) slightly by 1 percent.

The remainder of the paper is organized as follows. Section 2 provides a literature review. Section 3 lays out a trade model with endogenous skill formation. Section 4 constructs regional export demand shocks following the model. Section 5 describes the data set and summary statistics. Section 6 examines the effects of export expansions on school enrollment. Section 7 investigates the evolution of regional industry specialization resulting from trade-induced shifts in skill supply. Section 8 calibrates the model and studies the quantitative implications of further trade liberalization for China. Section 9 concludes the paper.

2 Related Literature

This paper relates to the literature on the dynamic Heckscher-Ohlin (HO) Model, which embeds endogenous factor formation into the classic HO framework. Seminal works include Stiglitz (1970), Findlay and Kierzkowski (1983) and Borsook (1987). The model predicts that trade increases the return to the abundant factor in a country, which induces further accumulation of this factor. Moreover, the amplified differences in factor abundance will in return strengthen a country's initial comparative advantage and industry specialization. Therefore, a country with abundant unskilled labor will be further deskilled and become more specialized in labor-intensive sectors after trade liberalization.

However, another strand of literature shows that trade can raise skill premium and hence encourage skill acquisition even in the context of developing countries (Burstein and Vogel, 2012; Harris and Robertson, 2013; Danziger, 2014). According to Burstein and Vogel (2012), a reduction in trade costs induces within-sector reallocation of production toward more productive and skill-intensive firms, which reinforces (counteracts) the HO forces in skill-abundant (skill-scarce) countries. Under certain parameters, they show that trade liberalization increases skill premium even in developing countries. Harris and Robertson (2013) build a model endogenizing capital and skill formation. In their setting, capital and skilled labor are complementary in production and trade liberalization increases the return to capital. Calibrated to data of China and India, the model predicts that skill premium increases in response to the tariff removal, which generates substantial accumulation of human capital in both countries. My findings of the negative impact of low-skill export shock on skill acquisition should not be taken as a rejection of the models emphasizing within-sector reallocation and capital accumulation mechanisms. Instead, the findings in this paper suggest that the between-sector Stolper-Samuelson effect appears to be strong.[2]

Relatively few empirical studies attempt to estimate the effects of trade on human capital formation. Edmonds and Pavcnik (2005) investigate the reduction of child labor associated with the rising price of rice when Vietnam removed its sanctions on rice exports. Edmonds, Pavcnik and Topalova (2010) examine the adverse effects of import competition on children's schooling following India's tariff reform in the 1990s. Both studies focus on young children[3] and find dominating income effects, i.e. trade policies alter household income which in turn affects child labor supply.

My paper shares more similarities with works by Blanchard and Olney (2014) and Atkin (2015), which show that the skill intensity of exports matters. In particular, using cross-country panel data and a gravity based instrumental variable (IV) technique, Blanchard and Olney (2014) show that export expansion in the agricultural and low-skill manufacturing sectors reduces average years of schooling whereas export expansion in the high-skill manufacturing sector increases it. Employing Mexican micro-level data, Atkin (2015) finds that the arrival of less-skilled export manufacturing jobs increases school dropouts at age 16. This paper attempts to build on these earlier contributions by bringing in several additional elements. First, I develop a theoretically consistent approach to study the causal effect of export expansions on skill acquisition. Guided by the model, I construct regional high-skill and low-skill export demand shocks, and carefully study their differential effects on schooling. Second, I draw on a rich sub-national data set that addresses the potential problem of endogeneity. Although the context of the study is a developing country, the vast geographic diversity of China allows me to examine the effects of export shocks on regions that are initially skill abundant. Third, I take a further step and investigate the feedback effect of trade-induced human capital accumulation or decumulation on regional industry specialization.

This paper also fits in the rapidly growing literature that employs the variation in regional initial differences in industry composition to study the differential effects of trade on local economies within a country, including Topalova (2010), Hakobyan and McLaren (2010), Autor, Dorn and

[2]The models emphasizing within-sector reallocation and capital accumulation receive empirical challenges in the context of China. Using Chinese manufacturing firm data, Ma, Tang and Zhang (2014) find that firms become less capital intensive after exporting. To rationalize the findings, they propose a model of heterogeneous firms producing multiple products with different capital intensities. The model predicts that in a labor abundant country like China, exporting firms' capital intensities decline due to product churning, i.e., exporting firms allocate more resources to produce labor-intensive products.

[3]Edmonds and Pavcnik (2005) study the children aged 6–15 and Edmonds, Pavcnik and Topalova (2010) study the children aged 10–14.

Hanson (2013), Kovak (2013), Dix-Carneiro and Kovak (2015), and others. However, unlike these studies, which focus on import shocks, I am more interested in the export demand shocks generated by the rest of the world.

3 A Model with Endogenous Skill Supply

The framework has three building blocks. The first is a standard Roy model of education choice, which is built on the work of Lagakos and Waugh (2013), Hsieh et al. (2013) and Burstein, Morales and Vogel (2015). Second, I augment the multi-region and multi-sector Ricardian model in Costinot, Donaldson and Komunjer (2012) with multiple factors of production. Due to the variation in regional comparative advantage and sectoral skill intensities, the factor content of trade shocks differs across regions. Third, I embed the Roy model in the general equilibrium framework and examine the effects of reduction in trade barriers on skill premium and educational attainment.

Specifically, the model features multiple regions ($i = 1, ..., N$) and multiple sectors ($k = 1, ..., K$) with different levels of skill intensity. Production in each sector requires inputs from both skilled and unskilled workers. The total supplies of skilled and unskilled labor in region i are H_i and L_i. I assume that there is no migration among regions but workers are perfectly mobile across sectors.[4] Also, labor is inelasitically supplied.

A unit mass of workers are born at each unit of time, and each of them lives for a period of length T. At birth, each worker is endowed with a vector of "individual productivities", denoted by $\{z_h, z_l\}$, which represent the efficiency of being a skilled worker and an unskilled worker, respectively. By assumption, z_h and z_n are randomly drawn from the multivariate Fréchet distribution:

[4] I abstract away from internal migration for the transparency of the model. The potential confounding effects introduced by migration are examined in the empirical part of the paper. The assumption on migration across regions is the same as Autor, Dorn and Hanson (2013). Alternatively, as is shown in Galle, Rodríguez-Clare and Yi (2015), one can allow perfect migration within a country and assume that heterogeneous workers in some regions are more closely attached to some sectors. The latter framework also shows that a national-level trade liberalization has different effects across regions within a country and suggests a Bartik-style index of region-level trade shock for empirical analysis.

[5]

$$F(z_h, z_l) = exp[-(z_h^{-\frac{\kappa}{1-\nu}} + z_l^{-\frac{\kappa}{1-\nu}})^{1-\nu}].$$

The parameter $\kappa > 1$ determines the dispersion of efficiency units, with a higher value of κ corresponding to smaller dispersion. The parameter $\nu \in [0, 1)$ governs the correlation between z_h and z_l. A higher value of ν increases this correlation, and $\nu = 0$ corresponds to the case where z_h and z_l are independent. Every worker decides about whether to enter labor market right away as an unskilled worker with z_l efficiency units of labor, or spend a period of time φ receiving an education and become a skilled worker equipped with z_h efficiency units of labor.

3.1 Education Decision

The lifetime income of a skilled worker is $\int_{\varphi}^{T} w_{i,h} z_h e^{-rt} dt = \frac{w_{i,h}}{r}(e^{-r\varphi} - e^{-rT}) z_h$, and the lifetime income of an unskilled worker is $\int_{0}^{T} w_{i,l} z_l e^{-rt} dt = \frac{w_{i,l}}{r}(1 - e^{-rT}) z_l$, where $w_{i,h}$ and $w_{i,l}$ denote the wage per efficiency unit of skilled labor and unskilled labor respectively. In equilibrium, the marginal workers are indifferent between obtaining an education or not, and hence the school enrollment rate in region i is determined by

$$\pi_{i,h} = \Pr(z_h w_{i,h}(e^{-r\varphi} - e^{-rT}) \geq z_l w_{i,l}(1 - e^{-rT})) = \frac{1}{\mu_i^{-\frac{\kappa}{1-\nu}} + 1}, \tag{3.1}$$

where $\mu_i = \frac{e^{-r\varphi} - e^{-rT}}{1 - e^{-rT}} \frac{w_{i,h}}{w_{i,l}}$ summarizes the regional return to schooling, which is determined by the local skill premium $\frac{w_{i,h}}{w_{i,l}}$. Equation (3.1) shows that the school enrollment rate increases with the return to school. Furthermore, a larger value of κ, which implies higher density of workers at the margin, raises the responsiveness of schooling to μ_i. A higher value of ν, which lessens the role of comparative advantage, also increases this responsiveness. In the steady state, $\pi_{i,h}$ also has a interpretation of share of educated workers in region i. Then, the share of uneducated workers is $\pi_{i,l} = 1 - \pi_{i,h}$.

As is shown in Appendix A.2, the expected productivities of educated and uneducated workers

[5] We can interpret the vector of "individual productivities" as a random start of talents across two occupations, h and l. An individual needs to receive education for a period of length φ to launch a career in occupation h. This is a simplified version of the case in Hsieh et al. (2013). A similar setting can also be found in Lagakos and Waugh (2013) and Burstein, Morales and Vogel (2015).

in the steady state are

$$E(z_h|z_h > z_l/\mu_i) = \gamma\pi_{i,h}^{-(1-\nu)/\kappa} \quad \text{and} \quad E(z_l|z_l > z_h\mu_i) = \gamma\pi_{i,l}^{-(1-\nu)/\kappa},$$

where $\gamma = \Gamma(\frac{\kappa-1}{\kappa})$ is the gamma function evaluated at $(\kappa-1)/\kappa$. Then, the effective supplies of skilled labor and unskilled labor in the steady state are

$$H_i = (T-\varphi)\gamma\pi_{i,h}^{1-(1-\nu)/\kappa} \quad \text{and} \quad L_i = T\gamma\pi_{i,l}^{1-(1-\nu)/\kappa}. \tag{3.2}$$

According to Equation (3.2), the total skilled labor supply increases with the share of educated workers at a diminishing rate. Intuitively, higher education return induces workers who are relatively unproductive as educated workers to nonetheless select into school, which lowers the average productivity of skilled workers. For a similar reason, total unskilled labor increases with the share of uneducated workers at a decreasing rate.

3.2 Production and Trade

The production side of the model extends Costinot, Donaldson and Komunjer (2012) by including multiple factors of production. Each good k may come in an infinite number of varieties indexed by $\omega \in \Omega \equiv \{1, ..., +\infty\}$. Production of the ωth variety of good k requires inputs of both skilled labor ($h_{i,k}(\omega)$) and unskilled labor ($l_{i,k}(\omega)$) with the following technology

$$y_{i,k}(\omega) = \psi_{i,k}(\omega)h_{i,k}(\omega)^{\alpha_k}l_{i,k}(\omega)^{1-\alpha_k},$$

where $\psi_{i,k}(\omega)$ is the total factor productivity (TFP) of producing the ωth variety of good k in region i, and α_k is the income share of skilled labor, with $\alpha_1 < \alpha_2 < ... < \alpha_K$. I assume $\psi_{i,k}(\omega)$ is a random variable drawn independently for each triplet (i, k, ω) from the Fréchet distribution:

$$\Psi_{i,k}(\psi) = e^{-(\psi/\psi_{i,k})^{-\varepsilon}} \quad \text{with} \quad \psi_{i,k} > 0 \text{ and } \varepsilon > 1.$$

Note that the parameter of fundamental productivity in sector k, $\psi_{i,k}$, varies across regions, and the parameter ε captures intra-industry heterogeneity. The variable cost of producing ωth variety of good k in region i, $v_{i,k}(\omega)$, is then expressed by

$$v_{i,k}(\omega) = \frac{1}{\psi_{i,k}(\omega)} \Big(\frac{w_{i,h}}{\alpha_k}\Big)^{\alpha_k} \Big(\frac{w_{i,l}}{1-\alpha_k}\Big)^{1-\alpha_k}.$$

Firms in region i of sector k face an iceberg cost, $\tau_{ij,k}$, of selling to market j, i.e., they must ship $\tau_{ij,k}$ units of output for one unit to arrive in region j. It is assumed that $\tau_{ij,k} \geq 1 \; \forall \; j \neq i$ and $\tau_{ii,k} = 1$. Therefore, the marginal cost of selling each unit in market j is $v_{i,k}(\omega)\tau_{ij,k}$.

Markets are assumed to be perfectly competitive. Hence, for each variety of good k, region i can sell in region j at price $p_{ij,k}(\omega) = v_{i,k}(\omega)\tau_{ij,k}$. Consumers in region j opt to source individual varieties from the lowest cost location, which implies the prevailing price of ωth variety of good k, $p_{j,k}(\omega)$, satisfies

$$p_{j,k}(\omega) = \min_i \{v_{i,k}(\omega)\tau_{ij,k}\}.$$

3.3 Preferences

The representative consumer's utility in region j is defined over the goods from sector $k = 1, ..., K$ as

$$C_j = \prod_{k=1}^{K} C_{j,k}^{\beta_k},$$

where $\beta_k > 0$ is the exogenous preference parameter satisfying $\sum_{k=1}^{K} \beta_k = 1$ and $C_{j,k}$ is the total consumption of the composite good k in region j,

$$C_{j,k} = \Big(\sum_{i=1}^{N} \sum_{\omega \in \Omega_{ij,k}} c_{j,k}(\omega)^{(\sigma-1)/\sigma}\Big)^{\sigma/(\sigma-1)},$$

where $\sigma > 1 + \varepsilon$ is the elasticity of substitution between different varieties.[6] $\Omega_{ij,k} \equiv \{\omega \in \Omega | p_{ij,k}(\omega) = \min_{i'}\{p_{i'j,k}(\omega)\}\}$ is the set of varieties of good k imported by region j from region i. $c_{j,k}(\omega)$ is region j's consumption of ωth variety of good k. The consumption is determined by $c_{j,k}(\omega) = (\frac{p_{j,k}(\omega)}{P_{j,k}})^{1-\sigma}\beta_k E_j$, where E_j is the total expenditure of region j, and $P_{j,k} = (\sum_i^N \sum_{\Omega_{ij,k}} p_{j,k}(\omega)^{1-\sigma})^{1/(1-\sigma)}$ denotes the price index of sector k in region j.

[6]The restriction is a technical assumption that guarantees the existence of a well-defined CES price index.

3.4 Trade Flows

Trade is assumed to be balanced. Thus, $E_j = Y_j$ where Y_j denotes total income. As is shown in Appendix A.3, the value of exports of good k from region i to j, $X_{ij,k}$, is determined by

$$X_{ij,k} = \lambda_{ij,k}\beta_k Y_j,$$

where $\lambda_{ij,k}$ denotes the fraction of region j's expenditure on good k allocated to the goods produced in region i and satisfies the following equation:

$$\lambda_{ij,k} = \frac{(v_{i,k}\tau_{ij,k})^{-\varepsilon}}{\sum_{i'}(v_{i',k}\tau_{i'j,k})^{-\varepsilon}},$$

where $v_{i,k} = \frac{1}{\psi_{i,k}}\left(\frac{w_{i,h}}{\alpha_k}\right)^{\alpha_k}\left(\frac{w_{i,l}}{1-\alpha_k}\right)^{1-\alpha_k}$ is the average variable cost of producing good k in region i.

3.5 Steady State Equilibrium

Denote $Y_{i,k}$ be sector k's value of output in region i. National income is determined by the sum of sectoral value outputs, i.e. $\sum_k Y_{i,k} = Y_i$. In the steady state, the $N(K+5)$ endogenous variables $\{w_{i,h}, w_{i,l}, H_i, L_i, \{Y_{i,k}\}_{k=1,\dots,K}, Y_i\}_{i=1,\dots,N}$ state are determined by the following labor market clearing conditions:

$$w_{i,h}H_i = \sum_{k=1}^{K}\alpha_k Y_{i,k}, \tag{3.3}$$

$$w_{i,l}L_i = \sum_{k=1}^{K}(1-\alpha_k)Y_{i,k}, \tag{3.4}$$

the goods market clearing condition:

$$Y_{i,k} = \sum_{j=1}^{N}\lambda_{ij,k}\beta_{j,k}Y_j, \tag{3.5}$$

and the factor supply equations:

$$H_i = (T-\varphi)\gamma\left(\frac{1}{\left(\frac{1-e^{-rT}}{(e^{-r\varphi}-e^{-rT})}\frac{w_{i,l}}{w_{i,h}}\right)^{\frac{\kappa}{1-\nu}}+1}\right)^{1-(1-\nu)/\kappa}, \tag{3.6}$$

$$L_i = T\gamma\left(1 - \frac{1}{(\frac{1-e^{-rT}}{(e^{-r\varphi}-e^{-rT}),}\frac{w_{i,l}}{w_{i,h}})^{\frac{\kappa}{1-\nu}} + 1}\right)^{1-(1-\nu)/\kappa}. \qquad (3.7)$$

4 Export Demand Shocks to Regional Markets

In this section, I derive a theoretical link between export demand shocks from the rest of the world (ROW) and education decisions in China. This simple framework underlies the empirical measures of regional export shocks and the identification strategy.

4.1 Reduced Form Relation

The exogenous shocks in this model come from changes in iceberg costs, $\{\hat{\tau}_{ij,k}\}$, and changes in productivity, $\{\hat{\psi}_{i,k}\}$, where i is a region in China and j is a region in the ROW, and hats over variables denote log changes ($\hat{x} \equiv d\ln x$). To derive the reduced form relation, each region in China is treated as a small open economy, and hence the exogenous shocks to region i have no effect on the income level of other regions. I only consider the instantaneous response of school enrollment to the exogenous shocks so that $\hat{H}_i = \hat{L}_i = 0$.[7] As exact changes in iceberg cost, $\hat{\tau}_{ij,k}$, are not observable from data, for the purpose of empirical analysis, the iceberg cost of exporting good k from region i in China to region j in the ROW is assumed to take the form $\tau_{ij,k} = \tau_{j,k}\tilde{\tau}_{ij,k}$. Here $\tau_{j,k}$ captures the costs such as tariff, exchange rate, and institutions, which all exporters in China incur, and $\tilde{\tau}_{ij,k}$ represents the idiosyncratic costs that apply to region i, such as the local transportation infrastructure.

As is shown in Appendix B, the impact of external demand shocks induced by $\{\hat{\tau}_{j,k}\}$ on region i's school enrollment rate is as follows:

$$\hat{\pi}_{i,h} = -c_1 \sum_k h_{i,k} \sum_{j\in ROW} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{j,k} + c_2 \sum_k l_{i,k} \sum_{j\in ROW} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{j,k} + \nu(\{\hat{\psi}_{i,k}, \hat{\tilde{\tau}}_{ij,k}\}), \quad (4.1)$$

where $c_{i,1}, c_{i,2} > 0$ are general equilibrium scaling factors; $h_{i,k} \equiv H_{i,k}/H_i$ and $l_{i,k} \equiv L_{i,k}/L_i$ denote,

[7] Note that conditions (3.3)-(3.5) must be satisfied in any equilibrium, while conditions (3.6) and (3.7) only hold in the steady state. In deriving Equation (4.1), I consider the response of skill premium and school enrollment to exogenous shocks in the short run by disturbing Equations (3.3)-(3.5), while keeping the labor supply H_i and L_i constant. In the model, time is continuous and workers are continuously distributed, and hence the mass of a cohort born at an instant of time is zero. Therefore, a change in education decision of a specific cohort does not affect total factor supplies, i.e., $\hat{H}_i = 0$ and $\hat{L}_i = 0$.

respectively, sector k's employment share in skilled and unskilled labor of region i; The export demand shock to sector k is the sum of $\hat{\tau}_{j,k}$'s weighted by $\gamma_{ij,k}(1-\lambda_{ij,k})$, where $\gamma_{ij,k} \equiv X_{ij,k}/Y_{i,k}$ denotes the revenue share from market j for sector k in region i. On the one hand, as $\gamma_{ij,k}$ measures how important market j is as an outlet of good k from region i, a higher weight is assigned to $\hat{\tau}_{j,k}$ if $\gamma_{ij,k}$ is larger. On the other hand, $\lambda_{ij,k}$ captures the market share of region i's good k in market j, so a lower weight is assigned to $\hat{\tau}_{j,k}$ if $\lambda_{ij,k}$ is larger. Intuitively, a large $\lambda_{ij,k}$ indicates that region i has high productivity or low iceberg cost in sector k relative to all other regions. Hence, a small change in $\tau_{j,k}$ has little effect on export demand. $\nu(\{\hat{\psi}_{i,k}, \hat{\tilde{\tau}}_{ij,k}\})$ is the residual term subsuming the effect of productivity shocks $\{\hat{\psi}_{i,k}\}$ and idiosyncratic iceberg cost shocks $\{\hat{\tilde{\tau}}_{ij,k}\}$. The sectoral shocks are then aggregated to the regional level, using employment share as weights. Equation (4.1) implies that school enrollment increases more when the declines in iceberg cost are more pronounced in the sectors employing larger share of skilled labor. I consider the terms $\sum_k h_{i,k} \sum_{j\neq i} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{j,k}$ and $\sum_k l_{i,k} \sum_{j\neq i} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{j,k}$ as high-skill and low-skill export demand shocks. Industry-level supply shocks deriving from productivity changes are absorbed in the residual term.

This weighted-average structure resembles the empirical approach in the literature on the local effects of trade (Topalova, 2010; Edmonds, Pavcnik and Topalova, 2010; Autor, Dorn and Hanson, 2013; Kovak, 2013). However, trade shocks differ by skill levels, reflecting the different skill content embodied in different industries. This approach shares similarities with Dix-Carneiro and Kovak (2015).

4.2 Export Demand Shocks: From National to Local

In order to employ Equation (4.1) for empirical analysis, I make the following assumptions: (1) the general equilibrium scaling factor ($c_{i,1}$ and $c_{i,2}$) are the same across China's regions (i.e. $c_{i,1} = c_1$ and $c_{i,2} = c_2$); (2) $\lambda_{ij,k} \approx 0$, that is each region in China has small market share in region j in the ROW; and (3) $\frac{X_{i\ ROW,k}}{X_{CH\ ROW,k}} \approx \frac{E_{i,k}}{E_k}$, that is the share of region i in China's total exports of good k is approximated by the region's share of national employment in that industry. With these restrictions in place, the change in school enrollment in region i becomes

$$\hat{\pi}_{i,h} \approx \tilde{c}_1 \sum_k \frac{H_{i,k}}{E_{i,k}} \frac{E_{i,k}}{E_k} \frac{\Delta X_k}{H_i} - \tilde{c}_2 \sum_k \frac{L_{i,k}}{E_{i,k}} \frac{E_{i,k}}{E_k} \frac{\Delta X_k}{L_i} + \nu(\{\hat{\psi}_{i,k}, \hat{\tilde{\tau}}_{ij,k}\}), \tag{4.2}$$

where $\tilde{c}_1, \tilde{c}_2 > 0$; $E_{i,k}/E_k$ denotes the share of region i in China's employment of sector k; $H_{i,k}/E_{i,k}$ and $L_{i,k}/E_{i,k}$ denote the employment share of skilled and unskilled workers in sector k of region i, respectively; $\Delta X_k \propto \sum_{j \in ROW} X_{CHj,k}\hat{\tau}_{j,k}$ is the change in national exports induced by $\{\hat{\tau}_{j,k}\}$. The approximation is detailed in Appendix B.

Following Equation (4.2), the main measures of high-skill and low-skill export demand shocks are constructed as

$$\Delta Export_{it}^{LS} = \sum_k \frac{L_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta X_{kt}}{L_{i0}} \quad \text{and} \quad \Delta Export_{it}^{HS} = \sum_k \frac{H_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta X_{kt}}{H_{i0}}. \tag{4.3}$$

Note that the measures of export shocks are constructed as the interaction of the industry factor intensity, the regional initial industry composition, and export changes at the sectoral level. Specifically, to build the high-skill demand shock, the national export shock of sector k, ΔX_k, is apportioned to region i according to its share of national industry employment in the base period, E_{ik0}/E_{k0}. Then, this regional export expansion is attributed to high skilled labor according to the sector's skill intensity, H_{ik0}/E_{ik0}, and normalized by the amount of high skilled labor H_{i0}. By construction, $\Delta Export_{it}^{HS}$ represents export exposure in dollar per skilled labor. Similarly, $\Delta Export_{it}^{LS}$ represents export exposure in dollar per unskilled labor.

Exports of industries with different skill intensities expand by varying levels, and at varying times, inducing different export exposures of various types of workers across regions in China. As skill intensity reflects inherent technological requirements of an industry, it is similar across regions. Therefore, the differences in regional export shocks mainly stem from the differences in local industry composition in the base period. In addition, differences in skill intensity across sectors provide the identification of parameters c_1 and c_2.

5 Data

5.1 Local Economies

In the empirical analysis, a local economy is a prefecture, an administrative division in China ranking between province and county. Prefectures are matched across census years according to the 2005 administration division of China, so that the data have a geographic panel dimension.

There are 340 prefectures, with median land area of 13,152 km^2 and median population of 3.2 million in year 2000.

Under China's household registration system, most migrant workers have restricted access to public health, education and social services, which in effect imposes significant barriers on inter-regional labor mobility.[8] According to the 2000 census, less than 4.5% of the population aged between 16 and 59 changed their prefecture of residence during the previous five years. This number increased slightly to 4.8% in 2005.[9] In contrast, the five-year migration rate across states was around 12.5% for the US in 2000 (Kaplan and Schulhofer-Wohl, 2013) and the five-year migration rate across districts in India (a similar administrative division to prefecture) was around 13.5% in 2007 (Marden, 2015).

5.2 Population Censuses

I use data from a 1% subsample of the 1990 and 2000 China Population Censuses, and a 20% subsample of the 2005 China 1% Population Sampling Survey (mini census).[10] The census data contain information such as region of residence, migration, school enrollment, educational attainment, demographic characteristics, employment status, occupation, and industry.

Data on Education. As of 1986, Chinese law mandated nine years of compulsory schooling (six years of primary education and three years of junior secondary education). It also requires all children to attend school by the age of 7.[11] For most of the analysis, the sample is restricted to young people aged at least 16, who should have already finished compulsory schooling. Specifically, I separately examine school enrollment of people of high school age (16 to 18 years), and college age (19 to 22 years). School enrollment rates at the prefecture level are constructed for each age group.

Figure 2 shows national school enrollment rates by age over the census years. The improvement of school enrollment is remarkable. From 1990 to 2005, enrollment rates increased by 30.5 and

[8] Tombe and Zhu (2014) estimate the migration cost across province amounted to 1.5 times annual income in the 1995-2000 period, and declined slightly to 1.3 times annual income between 2000 to 2005.

[9] The figure computed is from 20% subsample of the 2005 China 1% Population Sampling Survey.

[10] The 2005 China 1% Population Sampling Survey is like a medium-term small-scale census. It surveys 1% of the population and the questionnaire is very similar to the regular censuses. In my sample, the number of observations in 2005 is around 20% of those in 1990 and 2000.

[11] Provinces had different effective dates for implementing the compulsory education law.

12.7 percentage points for high school and college respectively. These improvements are more or less evenly split between the periods 1990 to 2000 and 2000 to 2005. It is also worth noting that, although it is improving over time, the enforcement of compulsory schooling is imperfect, especially for junior secondary education. Figure 3 plots prefecture school enrollment rates against lag period's enrollment rates for both high school and college. Most of the prefectures lie above the 45° line, suggesting the improvement in school enrollment was a nationwide phenomenon. More importantly, there is large variation in the increase in school enrollment conditional on the same initial level.

Data on Industry Employment. To construct export shocks as defined in (4.3), I use the employment data from the 1990 census. The census records region of residence and industry of employment at 3-digit Chinese Standard Industrial Classification (CSIC) codes (1984 version). To study the industry reallocation in Section 7, I also collect prefecture employment data at 2-digit CSIC level for censuses 1990, 2000 and 2010, which are assembled and published by the provincial statistics bureaux.

5.3 Trade and Tariff Data

From the UN Comtrade Database, I obtain data on China's export and import values at 4-digit International Standard Industrial Classification (ISIC) level for years 1992, 2000 and 2005.[12] Data on China's export tariffs imposed by destination countries at 4-digit ISIC level are collected from the TRAINS Database. The tariff faced by Chinese exporters in a 4-digit ISIC industry k during year t is computed according to

$$Tariff^X_{kt} = \sum_c \frac{Export_{China,c,k,t-1}}{Export_{China,k,t-1}} Tariff_{ckt},$$

where $Tariff_{ckt}$ denotes the tariff imposed by country c on goods of industry k during period t. The tariffs are weighted by the country's share in China's total exports of good k in the lag period, $\frac{Export_{China,c,k,t-1}}{Export_{China,k,t-1}}$, and then aggregated to the industry level. These weights are constructed using the trade flow data from three years earlier. Data on import tariffs imposed by China on 4-digit ISIC industries are collected from the TRAINS Database. To match the trade and tariff

[12] 1992 is the first year when the ISIC export data is available for China from UN Comtrade.

data with sectoral employment data from the 1990 census, I concord them into 3-digit CSIC codes. All export and import data are inflated to 2005 US dollar using the Consumer Price Index from China Statistical Yearbooks.

5.4 Regional Export Demand Shocks

To build the empirical counterpart of the regional export demand shocks as is defined in (4.3), I first run the regression

$$\ln Export_{kt} = \beta \ln(Tariff^X_{kt}) + \gamma_k + \phi_t + \mu_{kt}, \tag{5.1}$$

where $Tariff^X_{kt}$ is the weighted export tariff of industry k in year t, and γ_k and ϕ_t are industry and year fixed effects. Then, the local export demand shocks are constructed according to

$$\Delta Export^{LS}_{it} = \sum_k \frac{L_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta \widehat{Export}_{kt}}{L_{i0}} \quad \text{and} \quad \Delta Export^{HS}_{it} = \sum_k \frac{H_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta \widehat{Export}_{kt}}{H_{i0}}.$$

where $\widehat{Export}_{k,t} = exp(\hat{\beta} \ln(Tariff^X_{kt}) + \hat{\gamma}_k + \hat{\phi}_t)$ is the exponent of the fitted value from regression (5.1). High skilled labor H is considered as the set of workers with college education or above, and low skilled labor L is considered as the set of worker with high school education or below.

Note that the exogeneity of the conventional Bartik-style instrument relies on the assumptions that other time-varying, region specific determinants of the outcome variable are uncorrelated with (1) a region's initial industry composition, and (2) industry shocks at the national level. The latter requirement could be violated if an industry clusters in a specific region and the region also specializes in that industry. The above strategy potentially addresses this concern, as shocks at the national level are induced by external demand shocks from the ROW due to changes in export tariffs, which are deemed to be exogenous.

Panel B in Table 1 shows the descriptive statistics of export demand shocks, $\Delta Export^{LS}$ and $\Delta Export^{HS}$, by time period. The mean low- and high-skill shocks from 1990 to 2000 are \$183 and \$311, respectively. Export growth accelerated between 2000 and 2005, with mean low-skill and high-skill shocks being \$542 and \$916. Because of the substantial geographic differences in industry composition, the variation in export exposure is large across prefectures. The difference in low-skill export shock between prefectures at the 25th and 75th percentile was \$171 during the first period, and \$503 in the second period. For high-skill export expansion, the differences amounted to \$419 and \$1194, respectively. Panels A and B of Figure 1 show the distribution of low-skill and high-skill export demand shocks across prefectures in China during period 2000 to 2005. Prefectures are outlined in gray and provinces are outlined in black. Notice that export shocks are larger in the east of the country, where the prefectures are geographically smaller. The differences of the high-skill and low-skill shocks, i.e., $\Delta Export^{HS} - \Delta Export^{LS}$, are displayed in Panel C. The differential export shocks, ranging from -\$263 to \$1077, reflect industry specialization across prefectures. The differences across prefectures are stark, even within a province.

5.5 Industry Output and Other Socioeconomic Data

Data on industry output come from Chinese Industrial Annual Survey. Other socioeconomic variables at the prefecture level, including GDP per capita, fiscal expenditure on education, sex ratio, and share of population with urban Hukou, come from various provincial statistical yearbooks and population censuses. The distance to the nearest port for each prefecture is calculated using information from the World Port Index. More details about the data sources can be found in Appendix C.

6 Effects of Export Demand Shocks on School Enrollment

This section examines the effects of export demand shocks on high school and college enrollments following the framework outlined in Section 4.2 and using the export demand shocks constructed in Section 5.4. The estimation strategy identifies the effects of export expansion induced by the reduction in export tariff on the education decision. The identification relies on the assumption that the changes in export tariff are uncorrelated with the prefecture-specific shocks to industry productivity and trade costs.

6.1 Baseline Results

I evaluate the effects of export shocks on school enrollment by estimating the following equation:

$$\Delta Enroll_{it} = \beta_{LS}\Delta Export_{it}^{LS} + \beta_{HS}\Delta Export_{it}^{HS} + \phi_{pt} + \varepsilon_{it}, \tag{6.1}$$

where $\Delta Enroll_{it}$ is the change in school enrollment in the prefecture i between $t-1$ and t. The regression stacks the first differences for the two periods, 1990 to 2000 and 2000 to 2005, and includes province×year dummies (ϕ_{pt}). By introducing ϕ_{pt}, I flexibly account for the province-specific shocks in different periods, and hence the identification comes from within-province variation in export exposure. In all regressions, standard errors are clustered at the province level to account for the potential serial correlation over time and across prefectures within a province.

The results of the baseline regression (6.1) are presented in Column (1) of Table 2. Panel A and Panel B report the results for high school enrollment (age group 16–18) and college enrollment (age group 19–22), respectively. Export demand shocks have statistically significant effects on school enrollment. Specifically, a \$1000 increase in export per unskilled worker reduces the high school enrollment rate by 5.8 percentage points and decreases the college enrollment rate by 2.1 percentage points. Conversely, a \$1000 increase in export per skilled worker raises enrollment rates by 0.8 percentage point for high school and 1.2 percentage point for college. Column (2) incorporates a set of concurrent socioeconomic shocks that might independently affect education choices. It includes change in log GDP per capita, change in log fiscal expenditure, change in average age, change in the proportion of boys, and change in the proportion of population with urban Hukou. These controls leave the main results unaffected. Column (3) additionally includes the start-of-the-period school enrollment rate and log GDP per capita to account for the prefecture-specific trends that may correlate with the initial conditions of education and economic development. Again, the regression results remain stable.

A potential threat to the identification strategy is that the unobserved time-varying prefecture-specific determinants of school enrollment may correlate with a prefecture's initial industry structure. For example, if the prefectures initially specializing in high-skill industries receive a larger supply shock in education provision than the prefectures initially specializing in low-skill industries, the results will be confounded. To address this concern, Column (4) introduces two additional control variables constructed as follows

$$PLI_{i0} = \sum_{k \in Tr} \frac{L_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{i0}} \quad \text{and} \quad PHI_{i0} = \sum_{k \in Tr} \frac{H_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{i0}}.$$

where PLI_{i0} and PHI_{i0} stand for prefecture i's low-skill and high-skill intensity in the base period, respectively. These controls serve two purposes. First, the sum of PLI_{i0} and PHI_{i0} equal to the employment share of the tradable sector of prefecture i in the base period. Hence their inclusion isolates the variation of export demand shocks stemming from the within-tradable sector industry composition from the variation arising from the importance of tradable sector for local employment. Second, given the same size of tradable sector, a larger PHI_{i0} indicates that a prefecture is more specialized in high-skill industries. Therefore, the inclusion of PLI_{i0} and PHI_{i0} captures the initial differences in industry specialization. It is found that the estimates are insensitive to these controls.

Instead of explicitly controlling for the initial industry composition, Column (5) augments the regression model with prefecture dummies, which effectively accounts for the prefecture-specific linear time trend of school enrollment. As a result, the coefficients are identified through the time variation of export shocks within a prefecture. The results remain similar to those in Column (4), which alleviates the concern that the estimates are confounded by the different secular trends across prefectures that are associated with the initial industry specialization.

Column (6) replaces the change in school enrollment (a flow variable) with the change in educational attainment (a stock variable) as dependent variable. The dependent variable in Panel A is change in the share of population aged 16 to 18 with some high school education or above, and the dependent variable in Panel B is change in the share of population aged 19 to 22 with some college education or above. The estimates remain qualitatively similar. Quantitatively, however, the effects of low-skill export demand shock on educational attainment are smaller in magnitude than the effects on school enrollment. This finding provides suggestive evidence that a low-skill export shock not only discourages young people from proceeding onto high school/college, but also increases the dropout rate of those in high school/college.

To gauge the magnitude of the estimated effects of export demand shocks, we can consider the differential changes in school enrollments associated with the interquartile ranges of low-skill and high-skill export shocks between 1990 and 2005 (which were, respectively, \$681 per low skill worker and \$1600 per high skill worker). The point estimates in Column (4) imply that the high school and college enrollment rates in the prefectures at the 25th percentile of $\Delta Export^{LS}$ increased, respectively, by 2.3 and 2.1 percentage points more than those in the prefectures at the 75th percentile. Similarly, the high school and college enrollment rates in prefectures at the 25th percentile of $\Delta Export^{HS}$ increased, respectively, by 0.8 and 1.1 percentage points less than those in the prefectures at the 75th percentile.

6.2 Robustness

Export Expansions in Other Prefectures. The identification strategy relies on the assumption that only the local labor market condition is relevant to the education decision. Nevertheless, the locations of education and employment could be separate in the sense that an individual attains more or less education locally in response to export shocks elsewhere. Two approaches are adopted to investigate the effects of non-local export shocks:

(a) I construct the weighted average of export shocks of the neighboring prefectures according to:

$$\Delta Export_{it}^{s,N} = \sum_{r \in Neighbor_i} \theta_{ir} \Delta Export_{rt}^{s},$$

where $Neighbor_i$ denotes the set of prefectures sharing a border with prefecture i and $\theta_{ir} = \frac{E_{r0}}{\sum_{r' \in Neighbor_i} E_{r'0}}$ is the employment share of prefecture r among the neighboring prefectures of i.

(b) Controlling for neighboring prefectures' export shocks may not be sufficient, as an individual could respond to the expansion of a distant export manufacturing hub. Alternatively, I employ the inverse spatial distance among prefectures, to weight and aggregate the shocks of all other prefectures as follows

$$\Delta Export_{it}^{s,N} = \sum_{r \neq i} \frac{1}{d_{ir}} \Delta Export_{rt}^{s},$$

where d_{ir} denotes the distance between prefectures i and r.[13]

Table 3 presents the regression results incorporating the controls $\Delta Export_{it}^{s,N}$. The left and right panels give the results for approaches (a) and (b), respectively. Regardless of which way the

[13] I normalize the distance so that min(d_{ir})=1. As a result, the distance measure does not carry any unit.

non-local export shock is constructed, the estimated effects of local export shocks are insensitive and resemble those in Table 2. These findings suggest that the local labor market condition affects educational choice independently of cross-border spillovers. In addition, low-skill non-local export shocks are found to have an adverse effect on local school enrollment in most specifications. When constructed following approach (b), high-skill non-local export shocks are estimated to have positive effects on local school enrollments.

Import Shocks. An important element missing in the analysis thus far is the importance of imports from the ROW into China. In Table 4, I add import shocks $\Delta Import_{it}^{LS}$ and $\Delta Import_{it}^{HS}$ to the regression analysis. These shocks are constructed in a similar way to the export shocks discussed in Section 5.4, with data on exports and export tariffs replaced by imports and import tariffs. As is predicted by the model, a low-skill import shock increases the skill premium and hence raises the school enrollment rate, and the opposite is the case for a high-skill import shock. As shown in Columns (1) and (4), a \$1000 low-skill import shock enhances high school and college enrollment rates by 1.1 and 1.7 percentage points respectively. A \$1000 high-skill import shock depresses high school and college enrollment rates by 0.2 and 0.2 percentage point respectively. Columns (2) and (5) augment the specification with the controls PLI and PHI. The estimates remain statistically significant at conventional levels for both age groups, with the exception of high school enrollment in the case of low-skill import shock.

An issue with measuring exposure to import competition is that the imports to China not only include final goods purchased by domestic consumers, but also intermediate inputs and capital goods purchased by firms. The latter may substitute or complement the skilled or unskilled workers, shifting the skill demand and altering education incentives. If this is the case, the estimated impacts of import shocks may pick up effects other than import competition. To isolate the potential confounding effects introduced by imports of intermediate and capital goods, Column (3) and (6) include the controls $\Delta Import_{it}^{LS,CI}$ and $\Delta Import_{it}^{HS,CI}$, which measure the exposure to imports of intermediate and capital goods per low skilled worker and per high skilled worker.[14] Conditional on the import shocks of intermediate and capital goods, the low-skill and high-skill import shocks are found to have opposite and statistically significant effects on the school enrollments, as predicted by import competition.

[14] The intermediate inputs and capital goods are defined according to UNCTAD SoP product groups.

Although the measures of import shocks are potentially subject to endogeneity issues[15], the opposite effects of the export and import shocks detected in Table 4 are reassuring. Moreover, compared to Table 2, the estimated coefficients of export demand shocks change little. This finding alleviates the concern that the measures $\Delta Export_{it}^{s}$ may in part pick up import shocks, if the sectors experiencing larger export shocks are also the ones experiencing larger import shocks.

Selective Migration. The results could be confounded by selective migration. It is plausible that low-skill export expansions lower the average education of immigrants and increase the average education of out-migrants. The converse could be true for the case of high-skill export expansion. If it is the case, export shocks could change the average education level of the labor force by altering the composition of migrants. In Appendix D.1, I investigate the effects of the regional export shocks on the migration flows of workers with different education levels, and find suggestive evidence for the selective migration. Nevertheless, I show that this does not seem to quantitatively affect the effects emphasized by my model.

To evaluate the potential bias introduced, I estimate Equation (6.1) separately for each age group between 18 and 35 with the dependent variable replaced by the change in educational attainment. The idea is that if export demand shocks indeed affect the education choices through altering the contemporary labor market condition, the effects should be larger among the school age young people than in the older groups, as the education decision of the latter groups was made prior to the shocks. However, if instead the estimates of β_s are driven by selective migration, it should be expected that low- and high-skill shocks have similar effects on all age groups, if migration costs are similar for the young workers. The estimates and the 95% confidence intervals are plotted in Figure 4. The upper panel shows the effects of low- and high-skill export shocks on the share of the population with some high school education, and the lower panel shows the results for college

$\Delta Import_{it}^{LS,CI}$ and $\Delta Import_{it}^{HS,CI}$ are constructed according to

$$\Delta Import_{it}^{LS,CI} = \sum_{k} \frac{L_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta \widehat{Import}_{kt}^{CI}}{L_{i0}} \quad \text{and} \quad \Delta Import_{it}^{HS,CI} = \sum_{k} \frac{H_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta \widehat{Import}_{kt}^{CI}}{H_{i0}},$$

where $\widehat{Import}_{kt}^{CI}$ denotes the change in imports of capital and intermediate goods belonging to industry k, which is predicted by the changes in import tariffs. More details can be found in the Appendix C.

[15] Unlike export tariffs which are imposed by other countries, import tariffs are set by Chinese government and may be part of a well-planned development strategy. In such a scenario, changes in import tariffs across industries could systematically correlate with industry productivity shocks.

education attainment. Consistent with the findings in Table 2, export shocks have statistically significant effect on the educational attainment of school age young people. However, the effects are greatly dampened from age 23 onwards. This finding suggests that estimates of β_s are unlikely to be severely biased by selective migration.

Inflows of migrants could also dilute the educational effect of export expansion on local young people if, for example, the expansion of low-skill exports attracts low-skilled immigrants, offsetting the negative effect of the shocks on local skill premium. It is also possible that the local labor market is segmented in such a way that the low-skill export manufacturing sector employs only migrant workers. In both scenarios, low-skill export expansion might have only a small effect on local education decisions. Appendix D.2 explores this possibility by estimating Equation (6.1) separately for the sample of non-migrants. It shows that their education decisions are responsive to both low- and high-skill export shocks. Moreover, the estimates of β_s are statistically similar to those of the baseline sample, which contains both locals and immigrants.

Other Robustness Checks. In Appendix D, I demonstrate the robustness of the basic results to many additional specifications. Specifically, Appendices D.3 and D.4 confirm that the main findings are not driven by a particular demographic group or region. Appendix D.5 shows that the school enrollment of young children subject to compulsory schooling was barely affected by export expansion during the sample periods. Appendix D.6 examines the effects of export shocks on the youth's labor market outcomes and finds a mirror pattern for the market employment. Lastly, Appendix D.7 disaggregates the measures of export exposure into low-, medium- and high-skill shocks, and obtains consistent results.

7 Effect of Change in Skill Supply on Industry Specialization

In the dynamic context of Findlay and Kierzkowski (1983), trade enlarges the differences in factor abundance, which reinforces the initial comparative advantage and industry specialization. This section investigates the effect of trade-induced human capital accumulation or decumulation on evolution of industry specialization. Specifically, I estimate the following equation

$$\begin{aligned}\Delta Share^{M}_{ikt} = & \sum_{K\in\{LS,MS,HS\}} \gamma_K \mathbf{1}(k\in K)\Delta HighSch.Enroll_{it-1} \\ & + \sum_{K\in\{LS,MS,HS\}} \delta_K \mathbf{1}(k\in K)\Delta College.Enroll_{it-1} + \mathbf{X}'_{\mathbf{ik,t}}\zeta + \psi_{pk} + \upsilon_{ikt}\end{aligned} \tag{7.1}$$

where $\Delta Share^{M}_{ik,t}$ is the change in employment share of industry k in the manufacturing sector of prefecture i during the period 2000 to 2010, $\Delta HighSch.Enroll_{it-1}$ and $\Delta College.Enroll_{it-1}$ are the changes in high school and college enrollments in prefecture i during the period 1990 to 2000, and $\mathbf{1}(k \in K)$ is a dummy variable equal to 1 if industry k belongs to industry group K, where K can be low-skill, medium-skill or high-skill.[16] The changes in school enrollment are allowed to have differential effects on industries belonging to different industry groups, which are captured by the coefficients γ_K and δ_K. The vector $\mathbf{X}'_{\mathbf{ik,t}}$ contains industry k's start-of-the-period employment share in prefecture i and its changes in employment share in the period 1990 to 2000. Province×industry fixed effects ψ_{pk} are included to capture unobserved provincial industry policies.

Changes in school enrollment in the previous decade could be endogenous. For example, an individual's educational choice could be adjusted in expectation of future changes in industry structure. Local government could also change educational provision to adapt to industrial planning. To address this potential endogeneity problem, in some specifications, I instrument the interaction terms $\mathbf{1}(k \in K)\Delta HighSch.Enroll_{it-1}$ and $\mathbf{1}(k \in K)\Delta College.Enroll_{it-1}$ with $\mathbf{1}(k \in K)\Delta Export^{LS}_{it-1}$ and $\mathbf{1}(k \in K)\Delta Export^{HS}_{it-1}$. The IV regressions thus estimate the impact of export-induced changes in skill supply on the change in industry specialization in the later decade. The identification relies on the assumption that unobserved shocks affecting the evolution of industry specialization in the 2000s are uncorrelated with local industry composition in 1990 and export tariff changes during the 1990s.

The regression results are presented in Table 5. The OLS and 2SLS estimates are shown in Columns (1) and (2) respectively. Both find a significant effect of changes in college enrollment between 1990 and 2000 on changes in industry employment in the period 2000 to 2010. The 2SLS

[16] The grouping of the manufacturing industries is discussed in Appendix C.

estimates imply that a 10 percentage point increase in college enrollment in the 1990s reduces the employment share of an industry belonging to low-skill group by 0.87 percentage point, and raises the employment share of an industry belonging to high-skill group by 0.78 percentage point over the period 2000 to 2010. These IV estimates are larger in magnitude than OLS estimates in Column (1). Columns (3) and (4) repeat the regressions in Columns (1) and (2), but replace the change in employment share with the change in output share in the manufacturing sector as dependent variable. The OLS estimates are insignificantly different from zero. However, the 2SLS results are close to those in Column (2), albeit less precisely estimated.

Thus far, the regression analysis has been restricted to industry composition within the manufacturing sector. To check the sensitivity of the results to the inclusion of non-manufacturing sector, in Columns (5) and (6), the dependent variable $\Delta Share_{ikt}$ is re-defined as the change in manufacturing industry k's share of total employment in prefecture i over the period 2000 to 2010. As is shown in Column (6), the estimates from the 2SLS regression are consistent with baseline results. As a robustness exercise, I substitute the high school/college enrollment rates with the share of population with some high school/college education in Equation (7.1) as independent variable, and repeat the exercise in Table 5. The details and the results are discussed in Appendix D.8. The basic results are robust when the flow measures of skill supply are replaced by the stock measures.

8 Counterfactual Analysis

This section uses the model proposed in Section 3 to address the following counterfactual questions: How did the trade liberalization in the past decades affect the aggregate welfare, income distribution and human capital accumulation across regions in China? What are the implications of further trade liberalization on regional divergence in educational attainment and industry specialization? Due to the lack of data on bilateral trade flows among prefectures and between prefectures and the ROW, the quantitative analysis below defines regions and industries at more aggregated level.

8.1 Counterfactual Proportional Changes

Let $\hat{x} \equiv x'/x$ denote the proportional change in any variable x between the initial and counterfactual equilibria. The following system of equations solves for changes in wages ($\hat{w}_{i,h}$,$\hat{w}_{i,l}$), income ($\hat{Y}_i$), sectoral output ($\hat{Y}_{j,k}$), trade flows ($\hat{\lambda}_{ij,k}$) and labor supply ($\hat{H}_i$, $\hat{L}_i$):

$$\hat{Y}_{i,k} Y_{i,k} = \sum_j \lambda'_{ij,k} \beta_k \hat{Y}_j Y_j \tag{8.1}$$

$$\lambda'_{ij,k} = \frac{\lambda_{ij,k} (\hat{w}_{i,h}^{\alpha_k} \hat{w}_{i,l}^{1-\alpha_k} \hat{\tau}_{ij,k})^{-\varepsilon}}{\sum_{i'} \lambda_{i'j,k} (\hat{w}_{i',h}^{\alpha_k} \hat{w}_{i',l}^{1-\alpha_k} \hat{\tau}_{i'j,k})^{-\varepsilon}} \tag{8.2}$$

$$\hat{w}_{i,h} = \hat{H}_i^{-1} \sum_k h_{i,k} \hat{Y}_{i,k} \tag{8.3}$$

$$\hat{w}_{i,l} = \hat{L}_i^{-1} \sum_k l_{i,k} \hat{Y}_{i,k} \tag{8.4}$$

$$\hat{H}_i = \Big(\frac{(\hat{w}_{i,h}/\hat{w}_{i,l})^{\frac{\kappa}{1-\nu}}}{\pi_{i,h} (\hat{w}_{i,h}/\hat{w}_{i,l})^{\frac{\kappa}{1-\nu}} + (1 - \pi_{i,h})} \Big)^{1-(1-\nu)/\kappa} \tag{8.5}$$

$$\hat{L}_i = \Big(\frac{1}{\pi_{i,h} (\hat{w}_{i,h}/\hat{w}_{i,l})^{\frac{\kappa}{1-\nu}} + (1 - \pi_{i,h})} \Big)^{1-(1-\nu)/\kappa} \tag{8.6}$$

$$\sum_k \hat{Y}_{i,k} Y_{i,k} = \hat{Y}_i Y_i \tag{8.7}$$

The above system is derived from equilibrium conditions 3.3-3.7 and maps the exogenous changes in iceberg cost $\{\hat{\tau}_{ij,k}\}$ to outcomes $\{\hat{w}_{i,h}, \hat{w}_{i,l}, \hat{Y}_i, \hat{Y}_{i,k}, \lambda'_{ij,k}, \hat{H}_i, \hat{L}_i\}$, given parameters $\{\alpha_k, \beta_k, \varepsilon, \kappa, \nu\}$ and initial values $\{Y_{i,k}, Y_i, \lambda_{ij,k}, h_{i,k}, l_{i,k}, \pi_{i,h}\}$ from the data.

The solution to the above system can also be used to capture changes in other relevant objects, namely, school enrollment and aggregate welfare. It is straightforward to show that

$$\hat{\pi}_{i,h} = \frac{(\hat{w}_{i,h}/\hat{w}_{i,l})^{\frac{\kappa}{1-\nu}}}{\pi_{i,h} (\hat{w}_{i,h}/\hat{w}_{i,l})^{\frac{\kappa}{1-\nu}} + (1 - \pi_{i,h})}$$

$$\hat{C}_i = \prod_k (\hat{\lambda}_{ii,k})^{-\beta_k/\varepsilon} (\hat{w}_{i,h}^{\alpha_k} \hat{w}_{i,l}^{1-\alpha_k})^{-\beta_k}$$

8.2 Calibration

In this section, I calibrate the model to match fundamental moments in the data. The equilibrium system in Equations (8.1)-(8.7) takes parameters $\{\alpha_k, \beta_k, \varepsilon, \kappa, \nu\}$ and certain initial values $\{Y_{i,k}, Y_i, \lambda_{ij,k}, h_{i,k}, l_{i,k}, \pi_{i,h}\}$ as given. The parameters include the skill intensities of different sectors (α_k), the preference weight on goods from different sectors (β_k), and the parameters governing the firm productivity distribution (ε) and worker productivity distribution (κ and ν). The initial values include a region's sectoral outputs ($Y_{i,k}$), total income (Y_i), trade share ($\lambda_{ij,k}$), sectoral employment shares ($h_{i,k}$ and $l_{i,k}$), and school enrollment rate ($\pi_{i,h}$). I briefly discuss the calibration here and provide a summary in Table E.1. More details can be found in Appendix E.

Parameters Observable from Data. To calibrate the trade share $\lambda_{ij,k}$, I employ China's regional input-output (IO) data for the year 2007. The IO table provides data on the bilateral trade flows of 14 industries[17] between 8 regions in China and each region's trade with the ROW. A map of the regions is shown in Appendix E. With the trade flow data, I then calculate the expenditure share $\lambda_{ij,k} = X_{ij,k}/\sum_{i'} X_{i'j,k}$, where $X_{ij,k}$ denotes the spending by region j on good k from region i. The IO table also provides the data on sectoral output, $Y_{i,k}$, and total income, Y_i, for regions in China. The corresponding data from the ROW are obtained from the World Input-Output Database (WIOD) 2007, with the industries aggregated to the same level as China's regional IO data.

The data on sectoral employment share for skilled and unskilled labor ($h_{i,k}$ and $l_{i,k}$) are obtained from the 2005 mini census for regions in China, and from WIOD Socio Economic Accounts (WIOD SEA) 2007 for the ROW. For school enrollment rates, I employ data from the 2005 mini census for regions in China, and the 2005 data from Barro and Lee (2010) for the ROW. $\pi_{i,h}$ is calibrated as the share of population aged 20 to 24 with some college education. I assume that preferences and industry skill intensities are homogeneous across regions. α_k is calibrated as the income share of workers with some college education in industry k using data from the 2005 mini census. To calibrate β_k, I use China's regional IO table and calculate the expenditure share of each sector k for China as a whole. The values of calibrated α_k and β_k are shown in Table E.2.

[17] The original table contains 17 industries. I aggregate all the non-tradable industries into one sector. As a result, the modified table has 13 tradable industries and one non-tradable industry.

Trade Elasticity. Simonovska and Waugh (2014) propose an unbiased estimator for ε using a simulated method of moments. For the following quantitative analysis, I use their preferred estimate of $\varepsilon = 4.14$.

Calibration of Worker Productivity Distribution. Following the strategy adopted by Hsieh et al. (2013), I calibrate the parameter κ using within-group wage variation. As a worker's wage in the model equals the value of her marginal product, variation in individual productivity maps into variation in wages across workers. Let w_{zi} be the wage of individual z in region i. It is straightforward to show that in region i the wages of educated workers ($w_{zi}|Educ$) and uneducated workers ($w_{zi}|Uneduc$) follow the Fréchet distributions:

$$w_{zi}|Educ \sim \text{Fréchet}(w_{i,h}^{\kappa}\pi_{i,h}^{-(1-\nu)}, \kappa) \quad \text{and} \quad w_{zi}|Uneduc \sim \text{Fréchet}(w_{i,l}^{\kappa}(1-\pi_{i,h})^{-(1-\nu)}, \kappa)$$

Hence, the coefficient of variation of wages within a region$\times$education group in our model satisfies

$$CV^2 = \frac{Variance}{Mean^2} = \frac{\Gamma(1-2/\kappa)}{(\Gamma(1-1/\kappa))^2} - 1 \tag{8.8}$$

where $\Gamma(\cdot)$ denotes the gamma function. Hence, κ is implicitly determined by the within-group coefficient of variation of wage.

Income data come from the 2005 mini census. I restrict the sample to full-time salaried workers aged between 23 and 55 with monthly income of at least 300 RMB.[18] To estimate κ, I take residuals from the following cross-sectional regression

$$\ln w_{zg} = \rho_g + \mathbf{X}_{\mathbf{z}}'\xi + \varepsilon_{zg}$$

where $\ln w_{zg}$ is the log wage of individual z belonging to group g, ρ_g denotes region$\times$education group dummies, and $\mathbf{X}_{\mathbf{z}}$ is a vector of individual controls including dummies for age, gender, occupation, industry, marital status, urban residence status, workplace ownership type[19], and

[18] Full-time salaried workers are defined as those who are not self-employed and worked at least 30 hours in the previous week. In 2005, depending on a region's economic development, the minimum monthly wage ranged from 235 to 690 RMB across China.

[19] The workplace ownership type indicates whether an individual is working in a state-owned, collectively owned or privately owned enterprises.

working hours in the previous week. Then, I calculate the mean and variance of the exponent of these wage residuals, and solve κ numerically according to Equation (8.8). The point estimate of κ is 3.41.

The parameter ν, which governs the correlation of z_h and z_l, cannot be directly calibrated.[20] Hence, following Hsieh et al. (2013), I use $\nu = 0.1$ as the baseline value, and show that the main findings are not sensitive to the alternative values.

8.3 Eliminating External Trade

To investigate the effects of external trade liberalization in past decades across regions, I set trade costs between China's region and the ROW to infinity.[21] The counterfactual equilibrium is simulated using Equations (8.1)-(8.7). Table 6 displays the changes in educational attainment and gains from external trade. Most regions in China are found to have higher skill premium and hence higher educational attainment in the counterfactual where the external trade is shut down. The only exception is the North Municipalities, where school enrollment is higher relative to other regions and the ROW, which makes it more prone to receiving high-skill shocks when external trade is liberalized. The last column presents the gains from external trade, which are equal to the minus of the percentage changes in welfare. It shows that the gains from external trade are unevenly distributed across regions. Not surprisingly, coastal regions gain more from external trade. The most open region, the South Coast, enjoys an increase in welfare of 7.3% whereas the inland Central region only experiences a slight increase of 1.6%.

8.4 Further Trade Liberalization

As is established in Sections 6 and 7, surging trade in past decades exacerbated the differences in skill abundance across regions in China, which in turn reinforced regional comparative advantage and industry specialization. These findings suggest that ongoing globalization has important ramifications in terms of regional divergence in China. The general equilibrium effects of further

[20] The parameter ν captures the absolute advantage of an individual. Its calibration requires separate observations of the wages of educated and uneducated workers. However, from the available data, it is difficult to infer the counterfactual wage of an educated (uneducated) worker being an uneducated (educated) worker.

[21] i.e. $\hat{\tau}_{ij,k} = \begin{cases} +\infty & \text{if } i \neq \text{ROW} \ \& \ j = \text{ROW}; \\ +\infty & \text{if } i = \text{ROW} \ \& \ j \neq \text{ROW}; \\ 1 & \text{otherwise.} \end{cases}$

trade liberalization are analyzed in Table 7. Specifically, I lower the iceberg costs between China's region and the ROW by 30% and evaluate the effects on school enrollment and welfare. Columns (2) and (3) show the results of a uniform reduction in trade costs for all industries. Excepting the North Municipalities, most regions in China will experience a decline in skill premium and consequently educational attainment in the counterfactual. In addition, the gains from further trade liberalization are substantial. The coastal regions will experience increases in welfare of more than 15%. Even in the inland areas, welfare will rise by more than 5%.

China is expected to engage in more trade with other developing countries in the future, which will bring in positive high-skill demand shocks. To investigate the associated implications, I repeat the exercises in Columns (2) and (3), but only lower the external trade costs for the high-skill manufacturing industries by 30%.[22] Under this scenario, Central Coast, South Coast, and North Municipalities will see rises in skill premium and educational attainment, while the other regions will experience declines in skill premium and decumulation in human capital. A reduction of trade barriers for the high-skill industries will also generate sizable increases in welfare, ranging for 2.1% for North Coast to 9.6% for South Coast. Columns (6) and (7) repeat the exercises in Columns (2) and (3), but only lower the external trade costs for the low-skill manufacturing industries by 30%.[23] All regions in China will be deskilled by such a trade reform. Additionally, the increases in welfare are moderate, as shown in Column (7).

To better assess the effects of trade on regional divergence in educational attainment, I conduct the counterfactual analysis in Column (2) repeatedly, by gradually reducing the iceberg cost by 0 to 50%. The results are displayed in upper left panel of Figure 5, which plots the relation between proportional changes in school enrollment ($\hat{\pi}$) and the changes in iceberg cost ($\hat{\tau}$) across regions. Except in the North Municipalities, school enrollment declines as the iceberg cost is reduced. Moreover, educational attainment diverges across regions as trade liberalization deepens. The upper right panel corresponds to scenarios in which trade liberalization is restricted to high-skill industries, and the bottom left panel corresponds to scenarios in which trade liberalization is restricted to low-skill industries. The pattern of divergence is observed in both cases.

[22] The high-skill industries include Chemicals and Chemical Products, Machinery, Transportation Equipment, and Electrical and Optical Equipment.

[23] The low-skill industries include Textiles, Apparels, Footwear and Leather Products, Wood and Products of Wood and Cord, Non-Metallic Products, and Manufacturing, n.e.c..

9 Conclusion

By analyzing local labor markets that are subject to differential export demand shocks according to initial patterns of industry specialization, this paper examines the effects of export expansion on skill acquisition in China over the period 1990 to 2005. Export expansion is found to have differential effects on school enrollment, depending on a prefecture's initial industry composition. Prefectures initially specializing in high-skill industries experienced relatively faster human capital accumulation relative to prefectures initially specializing in low-skill industries. These findings suggest that the between-sector Stolper-Samuelson effect appears to be strong in the context of China. Moreover, trade-induced enlarged differences in skill abundance across prefectures reinforced initial industry specialization patterns.

The findings suggest that international trade could amplify the differences in skill abundance across countries due to the mutually reinforcing relationship between comparative advantage and skill formation. Although the benefits of international trade are often stressed, developing countries specializing in low-skill sector could experience a decline in education attainment when integrating into the world market. The present paper ignores externalities of education. However, if positive externalities of education are strong, the decumulation of human capital could undermine long-term gains from trade in a developing country. These considerations warrant future research on optimal policies balancing the trade-off between promoting educational attainment and increasing export growth in low-skill sectors in the context of developing countries.

References

Atkin, David. 2015. "Endogenous Skill Acquisition and Export Manufacturing in Mexico." Working Paper.

Auer, Raphael. 2010. "Are Imports from Rich Nations Deskilling Emerging Economies? Human Capital and the Dynamic Effects of Trade." Swiss National Bank (SNB) Working Paper.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *The America Economic Review* 103(6): 2121-2168.

Autor, David H., David Dorn, Gordon H. Hanson, and Jae Song. 2015. "Trade Adjustment: Worker-level Evidence." *The Quarterly Journal of Economics* 129(4): 1799-1860.

Balsvik, Ragnhild, Sissel Jensen, and Kjell G. Salvanes. 2015. "Made in China, Sold in Norway: Local Labor Market Effects of an Import Shock." *Journal of Public Economics* 127: 137-144.

Blanchard, Emily, and William W. Olney. 2014. "Globalization and Human Capital Investment: How Export Composition Drives Educational Attainment." Working Paper.

Bond, Eric W., Kathleen Trask, and Ping Wang. 2003. "Factor Accumulation and Trade: Dynamic Comparative Advantage with Endogenous Physical and Human Capital." *International Economic Review* 44(3): 1041-1060.

Borsook, Ian. 1987. "Earnings, Ability and International Trade." *Journal of International Economics* 22(3): 281-295.

Brandt, Loren, Johannes V. Biesebroeck, and Yifan Zhang. 2012. "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing." *Journal of Development Economics* 97(2): 335-351.

Burstein, Ariel, and Jonathan Vogel. 2012. "International Trade, Technology and the Skill Premium." Working Paper.

Burstein, Ariel, Eduardo Morales, and Jonathan Vogel. 2015. "Accounting for Changes in Between-Group Inequality." Working Paper.

Costinot, Arnaud, Dave Donaldson, and Ivana Komunjer. 2012. "What Goods Do Countries Trade? A Quantitative Exploration of Ricardo's Ideas." *Review of Economic Studies* 79(2): 581-608.

Danziger, Eliav. 2014. "Skill Acquisition and the Dynamics of Trade-Induced Inequality." Working Paper.

Dean, Judith M., and Mary E. Lovely. 2010. "Trade Growth, Production Fragmentation, and China's Environment." China's Growing Role in World Trade. Ed. R. Feenstra and S. Wei. Chicago: NBER and University of Chicago Press.

Dix-Carneiro, Rafael, and Brian K. Kovak. 2015. "Trade Liberalization and the Skill Premium: A Local Labor Markets Approach." *American Economic Review: Papers and Proceedings* 105(5): 551-557.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, Geography, and Trade." *Econometrica* 70(5): 1741-1779.

Ebenstein, Avraham, Margaret McMillan, Yaohui Zhao, and Chanchuan Zhang. 2012. "Understanding the Role of China in the "Decline" of US Manufacturing." Working Paper.

Edmonds, Eric V., and Nina Pavcnik. 2005. "The Effect of Trade Liberalization on Child Labor." *American Economic Journal: Applied Economics* 2(4): 42-75.

Edmonds, Eric V., Nina Pavcnik, and Petia Topalova. 2010. "Trade Adjustment and Human Capital Investment: Evidence from India Tariff Reform." *American Economic Journal: Applied Economics* 2(4): 42-75.

Findlay, Ronald, and Henryk Kierzkowski. 1983. "International Trade and Human Capital: A Simple General Equilibrium Model." *Journal of Political Economy* 91(6): 957-978.

Galle, Simon, Andrés Rodríguez-Clare and Moises Yi. 2015. "Slicing the Pie: Quantifying the Aggregate and Distributional Effects of Trade." Working Paper.

Han, Jun, Runjuan Liu and Junsen Zhang. 2012. "Globalization and wage inequality: Evidence from urban China" *Journal of International Economics* 87(2): 288-297.

Harris, Richard G., and Peter E. Robertson. 2013. "Trade, Wages and Skill Accumulation in the Emerging Giants" *Journal of International Economics* 89(2): 407-421.

Hsieh, Chang-Tai, Erik Hurst, Charles I. Jones and Peter J. Klenow. 2013. "The Allocation of Talents and U.S Economic Growth." Working Paper

Ma, Yue, Heiwai Tang and Yifan Zhang. 2014. "Factor Intensity, Product Switching and Productivity: Evidence from Chinese Exporters." *Journal of International Economics* 92(2): 349-362.

Marden, Samuel. 2015. "The Agriculture Roots of Industrial Development: 'Forward Linkages' in Reform Era China." Working Paper.

Hakobyan, Shushanik, and John McLaren. 2010. "Looking for Local Labor-Market Effects of NAFTA." NBER Working Paper 16535.

Kaplan, Greg, and Sam Schulhofer-Wohl. 2013. "Understanding the Long-Run Decline in Interstate Migration." Working Paper, Federal Reserve Bank of Minneapolis.

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

Lagakos, David, and Michael E. Waugh. 2013. "Selection, Agriculture, and Cross-Country Productivity Differences." *The America Economic Review* 103(2): 948-980.

Pierce, Justin R., and Peter K. Schott. 2012. "The Surprising Swift Decline of U.S. Manufacturing Employment." NBER Working Paper 18655.

Stiglitz, Joseph E.. 1970. "Factor Price Equalization in a Dynamic Economy." *Journal of Political Economy* 78(3): 456-488.

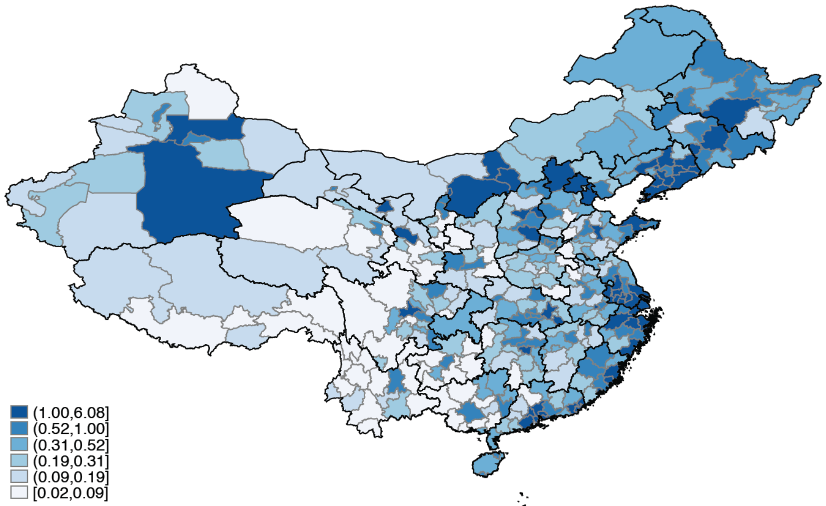
Simonovska Ina, Michael E. Waugh. 2014. "The Elasticity of Trade: Estimates and Evidence." *Journal of International Economics* 92(1): 34-50.

Topalova, Petia. 2010. "Factor Immobility and Regional Impacts of Trade Liberalization: Evidence on Poverty from India." *American Economic Journal: Applied Economics* 2(4): 1-41.

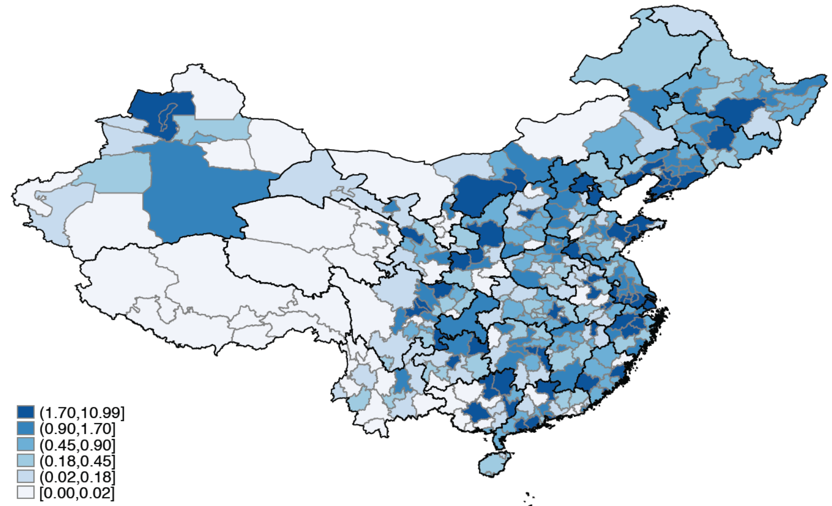
Tombe, Trevor, and Xiaodong Zhu. 2014. "Trade, Migration and Regional Income Differences: Evidence from China." Working Paper

Utar, Hale. 2014. "When the Floodgates Open: "Northern" Firms' Responses to Removal of Trade Quotas on Chinese Goods." *American Economic Journal: Applied Economics* 6(4): 226-250.

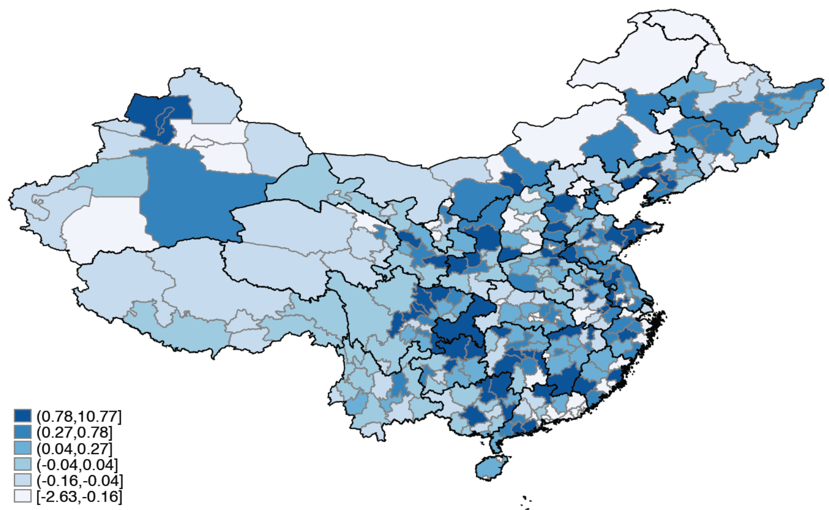
Figure 1: Spatial Distribution of Export Demand Shocks: 2000-05



Panel A: Export Shock: Low Skill



Panel B: Export Shock: High Skill



Panel C: Differential Export Shocks

Figure 2: School Enrollment by Ages over Years

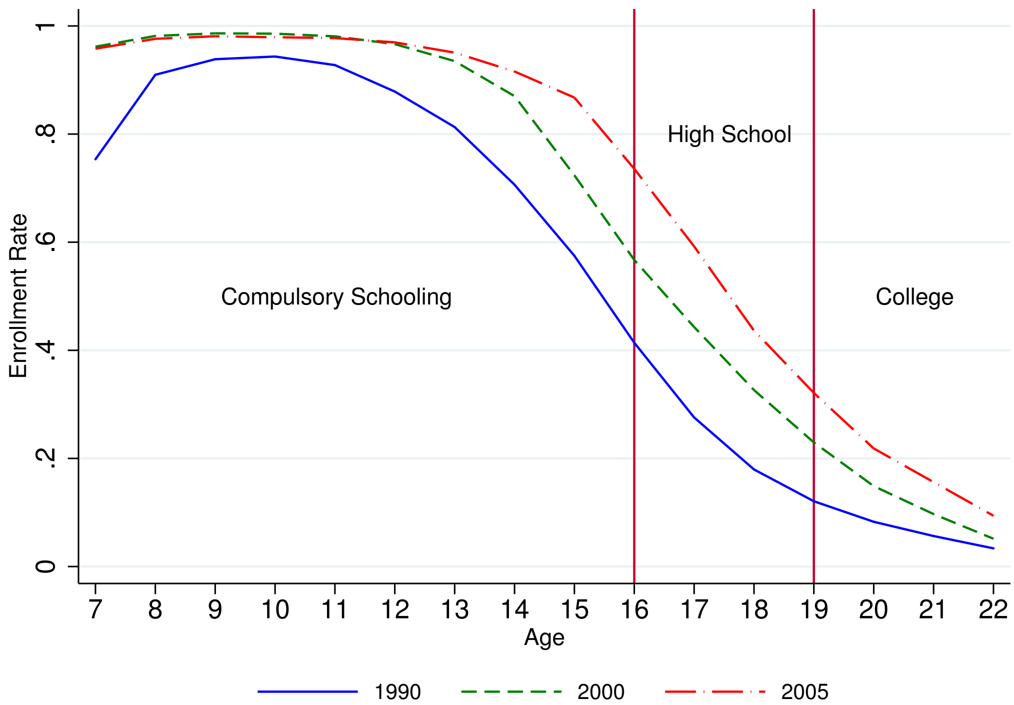


Figure 3: School Enrollment across Prefectures of Different Periods

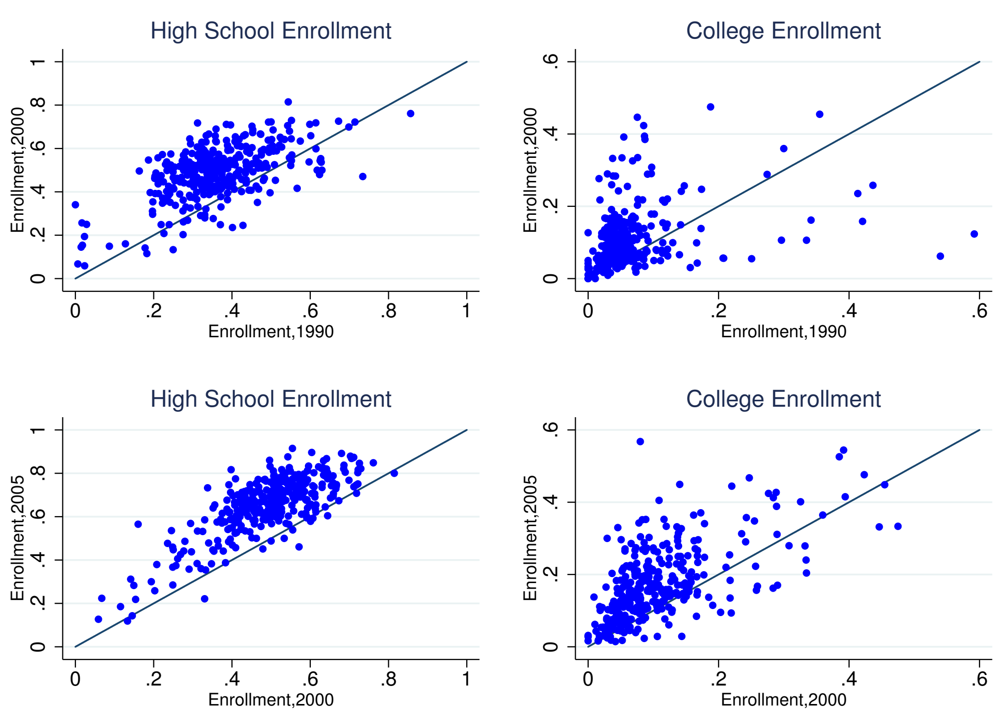
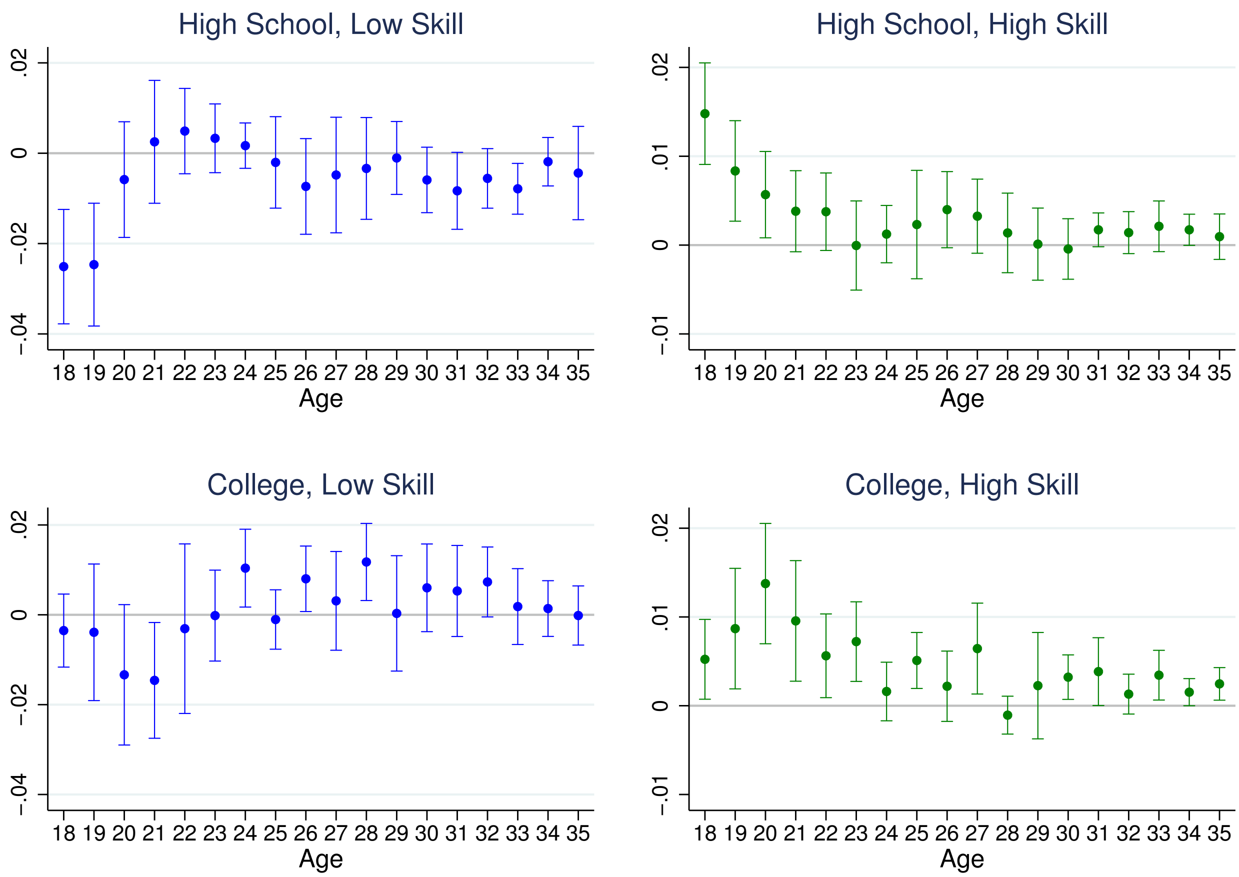


Figure 4: Change in Educational Attainment and Export Shocks:
Different Age Groups



Note: The upper panel shows the effects low/high-skill export shocks on high school education attainment. The lower panel shows the effects low/high skilled export shocks on college education attainment. All regressions are weighted by the start of the period prefecture's share of the age group population. All regressions control for the start-of-the-period share of population with some HS/college education and change in the log GDP per capita. Standard errors are clustered at province level.

Figure 5: Divergence in Education Attainment

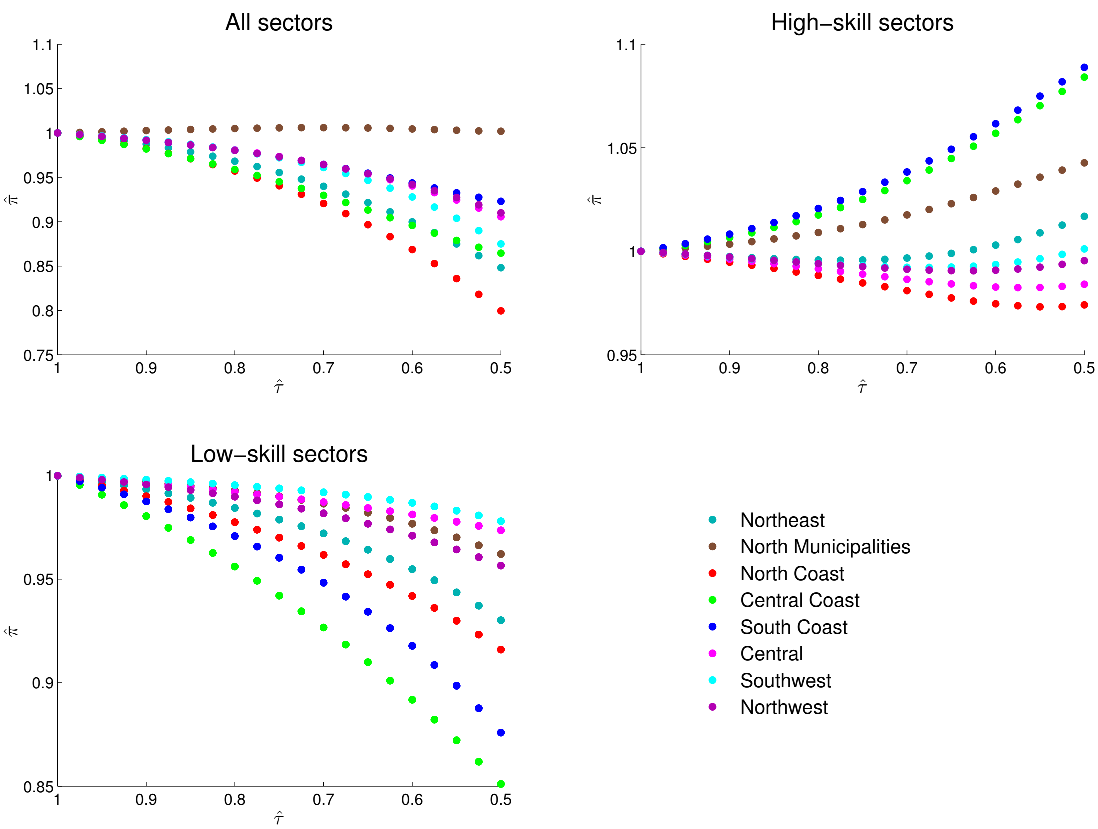


Table 1: Summary Statistics

	mean	std	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Change in School Enrollment: $\Delta Enroll$							
16-18, 90-00	0.124	0.113	-0.024	0.056	0.129	0.204	0.260
19-22, 90-00	0.043	0.090	-0.026	0.007	0.036	0.080	0.124
16-18, 00-05	0.156	0.098	0.026	0.089	0.164	0.223	0.281
19-22, 00-05	0.065	0.081	-0.017	0.016	0.057	0.111	0.166
16-18, 90-05	0.281	0.149	0.077	0.175	0.293	0.387	0.472
19-22, 90-05	0.108	0.111	0.010	0.042	0.098	0.159	0.250
Panel B: Export Shocks (1000USD): $\Delta Export$							
LS, 90-00	0.183	0.223	0.016	0.049	0.101	0.220	0.479
HS, 90-00	0.311	0.453	0.000	0.028	0.154	0.447	0.746
LS, 00-05	0.542	0.664	0.046	0.147	0.306	0.650	1.382
HS, 00-05	0.916	1.373	0.001	0.084	0.452	1.278	2.234
LS, 90-05	0.724	0.886	0.062	0.195	0.406	0.876	1.856
HS, 90-05	1.226	1.824	0.001	0.113	0.608	1.713	2.998

Notes: Number of prefecture is 340.

Table 2: Changes in School Enrollment and Export Shocks

	$\Delta Enroll$	$\Delta Enroll$	$\Delta Enroll$	$\Delta Enroll$	$\Delta Enroll$	$\Delta Highsch./$ $\Delta College$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Age 16-18						
$\Delta Export^{LS}$	-0.058***	-0.051***	-0.024**	-0.034***	-0.058**	-0.019*
	(0.014)	(0.008)	(0.009)	(0.011)	(0.028)	(0.009)
$\Delta Export^{HS}$	0.008***	0.007***	0.006***	0.005**	0.009**	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Province×Year	Y	Y	Y	Y	Y	Y
Controls		Y	Y	Y	Y	Y
Initial Conditions			Y	Y	Y	Y
PHI and PLI				Y		Y
Prefecture					Y	
N	680	673	673	673	673	673
R^2	0.399	0.644	0.681	0.693	0.924	0.857
Panel B: Age 19-22						
$\Delta Export^{LS}$	-0.021***	-0.021***	-0.019***	-0.031***	-0.039**	-0.023***
	(0.003)	(0.005)	(0.004)	(0.005)	(0.015)	(0.002)
$\Delta Export^{HS}$	0.012***	0.010***	0.010***	0.007***	0.010**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)
Province×Year	Y	Y	Y	Y	Y	Y
Controls		Y	Y	Y	Y	Y
Initial Conditions			Y	Y	Y	Y
PHI and PLI				Y		Y
Prefecture					Y	
N	680	673	673	673	673	673
R^2	0.145	0.597	0.695	0.761	0.920	0.770

Notes: All regressions are weighted by the start-of-the-period prefecture's age group population. Controls include change in average age, change in sex ratio, change in share of Han ethnic group, change in share of population with urban Hukou, change in log fiscal expenditure on education, and change in log GDP per capita. Initial conditions include the start of period school enrollment rate and log GDP per capita. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Changes in School Enrollment and Export Shocks: Controlling the Export Shocks of Other Prefectures

	(a) Neighbor Prefectures				(b) All Other Prefectures			
	Age 16-18		Age 19-22		Age 16-18		Age 19-22	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Export^{LS}$	-0.034***	-0.057**	-0.032***	-0.038***	-0.031***	-0.054*	-0.029***	-0.036**
	(0.010)	(0.025)	(0.004)	(0.013)	(0.010)	(0.028)	(0.005)	(0.016)
$\Delta Export^{HS}$	0.006***	0.009**	0.007***	0.011**	0.008***	0.012***	0.008***	0.011**
	(0.002)	(0.003)	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)	(0.005)
$\Delta Export^{LS,N}$	-0.004	-0.004	-0.005***	-0.007*	-0.053**	-0.062	-0.031***	-0.023
	(0.003)	(0.005)	(0.001)	(0.004)	(0.023)	(0.043)	(0.010)	(0.026)
$\Delta Export^{HS,N}$	0.001	0.000	-0.000	-0.001	0.037**	0.040*	0.017***	0.008
	(0.001)	(0.001)	(0.001)	(0.002)	(0.014)	(0.023)	(0.006)	(0.013)
Province×Year	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y	Y	Y
PHI and PLI	Y		Y		Y		Y	
Prefecture		Y		Y		Y		Y
N	673	673	673	673	673	673	673	673
R^2	0.695	0.924	0.767	0.923	0.703	0.926	0.764	0.920

Notes: All regressions are weighted by the start-of-the-period prefecture's age group population. Controls include change in average age, change in sex ratio, change in share of Han ethnic group, change in share of population with urban Hukou, change in log fiscal expenditure on education, and change in log GDP per capita. Initial conditions include the start of period school enrollment rate and log GDP per capita. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Changes in School Enrollment, Export Shocks and Import Shocks

	Age 16-18			Age 19-22		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Export^{LS}$	-0.027***	-0.036***	-0.023***	-0.023***	-0.033***	-0.033***
	(0.009)	(0.012)	(0.007)	(0.004)	(0.005)	(0.007)
$\Delta Export^{HS}$	0.007***	0.006**	0.006**	0.011***	0.008***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta Import^{LS}$	0.011*	0.007	0.015**	0.017*	0.008*	0.008*
	(0.006)	(0.007)	(0.006)	(0.009)	(0.004)	(0.005)
$\Delta Import^{HS}$	-0.002***	-0.001**	-0.002***	-0.002**	-0.001**	-0.001***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
$\Delta Import^{LS,CI}$			-0.054***			-0.016
			(0.012)			(0.016)
$\Delta Import^{HS,CI}$			0.001			-0.001
			(0.003)			(0.003)
Province×Year	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y
PHI and PLI		Y	Y		Y	Y
N	673	673	673	673	673	673
R^2	0.682	0.693	0.698	0.697	0.762	0.762

Notes: All regressions are weighted by the start-of-the-period prefecture's age group population. Controls include change in average age, change in sex ratio, change in share of Han ethnic group, change in share of population with urban Hukou, change in log fiscal expenditure on education, and change in log GDP per capita. Initial conditions include the start of period school enrollment rate and log GDP per capita. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Changes in Skill Supply and Change in Industry Specialization

	$\Delta Share^M$				$\Delta Share$	
	Employment		Output		Employment	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
$LS \times \Delta HighSch.Enroll_{t-1}$	0.025***	0.132***	-0.003	0.153	0.012***	0.080***
	(0.007)	(0.050)	(0.012)	(0.098)	(0.003)	(0.029)
$MS \times \Delta HighSch.Enroll_{t-1}$	-0.010	-0.020	-0.008	-0.078	0.001	0.017*
	(0.007)	(0.030)	(0.010)	(0.100)	(0.001)	(0.010)
$HS \times \Delta HighSch.Enroll_{t-1}$	-0.015**	-0.113**	0.013	-0.069	-0.003	-0.025**
	(0.006)	(0.046)	(0.011)	(0.092)	(0.002)	(0.012)
$LS \times \Delta College.Enroll_{t-1}$	-0.022***	-0.087***	-0.006	-0.088*	-0.009***	-0.063***
	(0.008)	(0.034)	(0.008)	(0.050)	(0.002)	(0.019)
$MS \times \Delta College.Enroll_{t-1}$	0.008	0.009	0.007	0.010	-0.002*	-0.020***
	(0.006)	(0.018)	(0.009)	(0.053)	(0.001)	(0.007)
$HS \times \Delta College.Enroll_{t-1}$	0.013**	0.078***	0.001	0.079*	-0.000	0.015*
	(0.006)	(0.030)	(0.011)	(0.042)	(0.002)	(0.009)
$\Delta ShareEmp^M_{t-1}$	Y	Y	Y	Y		
$\Delta ShareEmp_{t-1}$					Y	Y
Province×Ind	Y	Y	Y	Y	Y	Y
N	8,721	8,721	9,180	9,180	8,721	8,721

Notes: All regressions control for the start of the period industry employment/output share. Standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Counterfactual: Eliminating External Trade

Region	(1) π_{ih}	(2) $\frac{\hat{w}_{i,h}}{\hat{w}_{i,l}}$	(3) $\hat{\pi}_{ih}$	(4) $\%G$
Northeast	0.167	1.008	1.027	2.778
North Municipalities	0.452	0.993	0.986	6.353
North Coast	0.118	1.013	1.044	1.805
Central Coast	0.290	1.022	1.060	6.713
South Coast	0.136	1.007	1.024	7.300
Central	0.116	1.006	1.019	1.602
Southwest	0.088	1.005	1.016	2.792
Northwest	0.117	1.006	1.022	1.722

Notes: Gains from trade $\%G = (1 - \hat{C}) \times 100$.

Table 7: Counterfactual: Further Trade Liberalization

	All Ind.			High skill ind.			Low skill ind.		
	$\frac{\hat{w}_{i,h}}{\hat{w}_{i,l}}$ (1)	$\hat{\pi}_{ih}$ (2)	$\%C$ (3)	$\frac{\hat{w}_{i,h}}{\hat{w}_{i,l}}$ (4)	$\hat{\pi}_{ih}$ (5)	$\%C$ (6)	$\frac{\hat{w}_{i,h}}{\hat{w}_{i,l}}$ (7)	$\hat{\pi}_{ih}$ (8)	$\%C$ (9)
Northeast	0.981	0.940	8.347	0.999	0.997	4.275	0.991	0.972	1.724
North Municipalities	1.003	1.006	16.109	1.008	1.018	8.255	0.993	0.986	2.471
North Coast	0.976	0.920	5.562	0.994	0.981	2.148	0.988	0.962	1.285
Central Coast	0.974	0.930	15.212	1.013	1.034	6.996	0.972	0.927	3.382
South Coast	0.989	0.965	15.933	1.012	1.038	9.614	0.984	0.948	1.774
Central	0.989	0.964	5.003	0.996	0.986	3.283	0.996	0.987	0.765
Southwest	0.989	0.961	8.206	0.998	0.992	4.559	0.998	0.992	1.467
Northwest	0.989	0.964	5.541	0.997	0.991	3.521	0.995	0.982	1.009

Appendix

A Proofs

A.1 Share of Educated Workers

Note that the share of educated workers is determined by $\pi_h = \Pr(z_h \geq z_l/\mu)$. Let

$$G(z_h, z_l) = \partial F(z_h, z_l)/\partial z_l = exp[-(z_h^{-\frac{\kappa}{1-\nu}} + z_l^{-\frac{\kappa}{1-\nu}})^{1-\nu}]\kappa(z_h^{-\frac{\kappa}{1-\nu}} + z_l^{-\frac{\kappa}{1-\nu}})^{-\nu} z_l^{-\frac{\kappa}{1-\nu}-1}$$

then,

$$\pi_i = \int_0^\infty (1 - G(z_l/\mu, z_l))dz_l = 1/(\mu^{-\frac{\kappa}{1-\nu}} + 1).$$

A.2 Expected Productivity of Educated and Uneducated Workers

First, I show that after education decisions, the ex-post productivity of educated workers follows the distribution Fréchet($1 + \mu^{-\kappa}$,κ), and the ex-post productivity of uneducated workers follows the distribution Fréchet($1+\mu^{\kappa}$,κ). To see this, the distribution of productivity of educated workers is

$$\Pr(z_h \leq z | Educated) = \Pr(z_h \leq z | z_h \geq z_l/\mu) = \frac{\Pr(z_h \leq z, z_h \geq z_l/\mu)}{\Pr(z_h \geq z_l/\mu)}.$$

Note that

$$\Pr(z_h \leq z, z_h \geq z_l/\mu) = \int_0^{\mu z} (G(z, z_l) - G(z_l/\mu, z_l))dz_l = \frac{1}{1 + \mu^{-\frac{\kappa}{1-\nu}}} exp[-(1 + \mu^{-\frac{\kappa}{1-\nu}})^{1-\nu} z^{\kappa}].$$

As $\Pr(z_h \geq z_l/\mu) = \frac{1}{1+\mu^{-\frac{\kappa}{1-\nu}}}$, we have

$$\Pr(z_h \leq z | Educated) = e^{-(1+\mu^{\frac{-\kappa}{1-\nu}})^{1-\nu} z^{-\kappa}}.$$

Similarly, it can be shown that

$$\Pr(z_l \leq z | Uneducated) = e^{-(1+\mu^{\frac{\kappa}{1-\nu}})^{1-\nu} z^{-\kappa}}.$$

Therefore,

$$E(z_h | Educated) = \gamma \pi_h^{-(1-\nu)/\kappa} \quad \text{and} \quad E(z_l | Uneducated) = \gamma (1 - \pi_h)^{-(1-\nu)/\kappa}.$$

where $\gamma = \Gamma(1 - 1/\kappa)$. The supplies of skilled and unskilled labor are then determined by

$$H = (T - \varphi)\pi_h E(z_h|Educated) = (T - \varphi)\gamma\pi_h^{1-(1-\nu)/\kappa}$$

and

$$L = T(1 - \pi_h)E(z_l|Uneducated) = T\gamma(1 - \pi_h)^{1-(1-\nu)/\kappa}.$$

A.3 Prices and Trade Flows

Prices. For good k, the prices which region i presents to region j, $p_{ij,k}(\omega)$, follow the distribution $G_{ij,k}(p) = 1 - exp[-(v_{i,k}\tau_{ij,k})^{-\varepsilon}p^{\varepsilon}]$. As in Eaton and Kortum (2002), price distributions have three useful properties:

(a) For each good k, the probability that region i provides a variety at the lowest price in region j, $\lambda_{ij,k}$ satisfies

$$\lambda_{ij,k} = Prob(p_{ij,k}(\omega) = \min_{i'}\{p_{i'j,k}(\omega)\}) = \int_0^{\infty} \prod_{i' \neq i}[1 - G_{i'j,k}(p)]dG_{ij,k}(p) = \frac{(v_{i,k}\tau_{ij,k})^{-\varepsilon}}{\sum_{i'}(v_{i',k}\tau_{i'j,k})^{-\varepsilon}}.$$

(b) The price distribution of good k prevailing in region j is

$$G_{j,k}(p) = 1 - \prod_{i=1}^{N}(1 - G_{ij,k}(p)) = 1 - exp[-\sum_{i'}(v_{i',k}\tau_{i'j,k})^{-\varepsilon}p^{\varepsilon}].$$

Therefore, the price index of good k in region j is

$$P_{j,k} = (\sum_i (v_{i,k}\tau_{ij,k})^{-\varepsilon})^{-\frac{1}{\varepsilon}}\Gamma(\frac{\varepsilon + 1 - \sigma_k}{\sigma_k})^{\frac{1}{1-\sigma_k}}.$$

(c) The price of good k that region j actually buys from region i also has the distribution $G_{j,k}(p)$. To see this, conditional on the lowest price supplier being i, the price distribution of $p_{j,k}(\omega)$ satisfies

$$Prob(p_{j,k}(\omega) \leq p|p_{ij,k}(\omega) = \min_{i'}\{p_{i'j,k}(\omega)\}) = \frac{1}{\lambda_{ij,k}} \int_0^{p} \prod_{i' \neq i}[1 - G_{i'j,k}(q)]dG_{ij,k}(q) = G_{j,k}(p).$$

Trade Flows. The fraction of region j's expenditure on good k allocated to the goods produced in region i satisfies

$$\begin{aligned}\frac{X_{ij,k}}{X_{j,k}} &= \frac{\sum_{\omega\in\Omega}[p_{j,k}(\omega)\mathbf{1}(p_{ij,k}(\omega)=\min_{i'}\{p_{i'j,k}(\omega)\})]^{1-\sigma_k}}{\sum_{\omega\in\Omega}p_{j,k}(\omega)^{1-\sigma_k}} \\ &= \lambda_{ij,k}\frac{E[p_{j,k}(\omega)^{1-\sigma_k}|p_{ij,k}(\omega)=\min_{i'}\{p_{i'j,k}(\omega)\}]}{E[p_{j,k}(\omega)^{1-\sigma_k}]} \\ &= \lambda_{ij,k}\end{aligned}$$

where the second equality employs the strong law of large numbers for independent and identically distributed random variables and the continuous mapping theorem, and the last equality uses the properties (b) and (c) of price distributions. Therefore, $\lambda_{ij,k}$ denotes not only the share of varieties of good k consumed by region j that originate from region i, but also the expenditure of region j on good k from region i.

B Reduced Form Relation between Export Shocks and School Enrollment

This appendix shows how the export shocks affect school enrollment in prefecture i in the short run, by disturbing the equilibrium system (3.3)-(3.5) with the exogenous changes in iceberg cost $\hat{\tau}_{ij,k}$ ($\hat{\tau}_{ii,k}=0$) and productivity $\hat{\psi}_{i,k}$. In this section $\hat{x}\equiv\Delta\ln(x)=\Delta x/x$ denotes the percentage change in any variable x between the initial and new equilibrium. Each prefecture is treated as a small open economy, and by assumption, the export shocks to prefecture i have no effect on the wages and income levels of other regions. In addition, I only consider the short-term effect such that $\hat{H}_i=\hat{L}_i=0$.

B.1 Linearization

Taking log-linearization of Equations (3.3) and (3.4) obtains

$$\hat{w}_{ih}=\sum_k h_{i,k}\hat{Y}_{i,k} \tag{B.1}$$

$$\hat{w}_{il}=\sum_k l_{i,k}\hat{Y}_{i,k} \tag{B.2}$$

where $h_{i,k}$ and $l_{i,k}$ denote the share of skilled labor and unskilled labor allocated to sector k in region i, respectively. Taking log-linearization of equation (3.5) obtains

$$\begin{aligned}\hat{Y}_{i,k} &= -\varepsilon \sum_j \gamma_{ij,k}(1-\lambda_{ij,k})(\alpha_k \hat{w}_{i,h} + (1-\alpha_k)\hat{w}_{i,l} - \hat{\psi}_{i,k} + \hat{\tau}_{ij,k}) + \gamma_{ii,k}(\theta_i \hat{w}_{i,h} + (1-\theta_i)\hat{w}_{i,l}) \\ &= -\underbrace{(\delta_{i,k}\varepsilon\alpha_k - \gamma_{ii,k}\theta_i)}_{a_{i,k1}}\hat{w}_{i,h} - \underbrace{(\delta_{i,k}\varepsilon(1-\alpha_k) - \gamma_{ii,k}(1-\theta_i))}_{a_{i,k2}}\hat{w}_{i,l} + \delta_{i,k}\varepsilon\hat{\psi}_{i,k} - \varepsilon\hat{\tau}_{i,k}\end{aligned} \tag{B.3}$$

for each sector k. Here $\gamma_{ij,k}$ denotes prefecture i's revenue share in sector k that is from market j, and $\theta_i = \frac{w_{i,h}H_i}{w_{i,h}H_i + w_{i,l}L_i}$ is the income share of skilled workers in prefecture i. To simplify the notations, I define $\delta_{i,k} = \sum_j \gamma_{ij,k}(1-\lambda_{ij,k})$ and $\hat{\tau}_{i,k} = \sum_{j\neq i} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{ij,k}$.
The system of linear Equations (B.1)-(B.3) can be written in the matrix form:

$$\left[\begin{array}{cccc|cc} 1 & 0 & \dots & 0 & a_{i,11} & a_{i,12} \\ 0 & 1 & & \vdots & a_{i,21} & a_{i,22} \\ \vdots & & \ddots & 0 & \vdots & \vdots \\ 0 & \dots & 0 & 1 & a_{i,K1} & a_{i,K2} \\ \hline -h_{i,1} & -h_{i,2} & \dots & -h_{i,K} & 1 & 0 \\ -l_{i,1} & -l_{i,2} & \dots & -l_{i,K} & 0 & 1 \end{array}\right] \left[\begin{array}{c} \hat{Y}_{i,1} \\ \hat{Y}_{i,2} \\ \vdots \\ \hat{Y}_{i,K} \\ \hline \hat{w}_{i,h} \\ \hat{w}_{i,l} \end{array}\right] = \left[\begin{array}{c} \delta_{i,1}\varepsilon\hat{\psi}_{i,1} - \varepsilon\hat{\tau}_{i,1} \\ \delta_{i,2}\varepsilon\hat{\psi}_{i,2} - \varepsilon\hat{\tau}_{i,2} \\ \vdots \\ \delta_{i,K}\varepsilon\hat{\psi}_{i,K} - \varepsilon\hat{\tau}_{i,K} \\ \hline 0 \\ 0 \end{array}\right]$$

where $a_{i,k1} = \delta_{i,k}\varepsilon\alpha_k - \gamma_{ii,k}\theta_i$ and $a_{i,k2} = \delta_{i,k}\varepsilon(1-\alpha_k) - \gamma_{ii,k}(1-\theta_i)$. To solve for the endogenous variables $\hat{w}_{ih}$ and $\hat{w}_{il}$, the system is rewritten into more compact matrix notation

$$\left[\begin{array}{c|c} \mathbf{I}_{K\times K} & \mathbf{A}_{K\times 2} \\ \hline \mathbf{\Phi}_{2\times K} & \mathbf{I}_{2\times 2} \end{array}\right] \left[\begin{array}{c} \hat{\mathbf{Y}}_{K\times 1} \\ \hline \hat{\mathbf{w}}_{2\times 1} \end{array}\right] = \left[\begin{array}{c} \hat{\mathbf{S}}_{K\times 1} \\ \hline \mathbf{0}_{2\times 1} \end{array}\right].$$

Cramer's rule and the rule for the determinant of a partitioned matrix are used to solve for the changes in skilled and unskilled wages:

$$\hat{w}_{ih} = \frac{\det(\mathbf{X_h} - \mathbf{\Phi S_h})}{\det(\mathbf{I} - \mathbf{\Phi A})} \quad \text{and} \quad \hat{w}_{il} = \frac{\det(\mathbf{X_l} - \mathbf{\Phi S_l})}{\det(\mathbf{I} - \mathbf{\Phi A})}$$

$$\text{where} \quad \mathbf{X_h} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \quad \mathbf{X_l} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\mathbf{S_h} = \begin{bmatrix} \delta_{i,1}\varepsilon\hat{\psi}_{i,1} - \varepsilon\hat{\tau}_{i,1} & a_{i,12} \\ \delta_{i,2}\varepsilon\hat{\psi}_{i,2} - \varepsilon\hat{\tau}_{i,2} & a_{i,22} \\ \vdots & \vdots \\ \delta_{i,K}\varepsilon\hat{\psi}_{i,K} - \varepsilon\hat{\tau}_{i,K} & a_{i,K2} \end{bmatrix} \quad \mathbf{S_l} = \begin{bmatrix} a_{i,11} & \delta_{i,1}\varepsilon\hat{\psi}_{i,1} - \varepsilon\hat{\tau}_{i,1} \\ a_{i,21} & \delta_{i,2}\varepsilon\hat{\psi}_{i,2} - \varepsilon\hat{\tau}_{i,2} \\ \vdots & \vdots \\ a_{i,K1} & \delta_{i,K}\varepsilon\hat{\psi}_{i,K} - \varepsilon\hat{\tau}_{i,K} \end{bmatrix}.$$

It can be shown that

$$\begin{aligned} \hat{w}_{ih} - \hat{w}_{il} = & -\frac{\varepsilon \sum_k l_{i,k}(\delta_{i,k}\varepsilon - \gamma_{ii,k} + 1)}{\det(\mathbf{I} - \mathbf{\Phi A})} \sum_k h_{i,k}(-\delta_{i,k}\hat{\psi}_{i,k} + \hat{\tau}_{i,k}) \\ & + \frac{\varepsilon \sum_k h_{i,k}(\delta_{i,k}\varepsilon - \gamma_{ii,k} + 1)}{\det(\mathbf{I} - \mathbf{\Phi A})} \sum_k l_{i,k}(-\delta_{i,k}\hat{\psi}_{i,k} + \hat{\tau}_{i,k}) \end{aligned}. \tag{B.4}$$

The following proof shows that $\det(\mathbf{I} - \mathbf{\Phi A}) > 0$. To simplify the notations, the subscript i is dropped.

Proof: Note that $\det(\mathbf{I} - \mathbf{\Phi A}) = \sum_{k=1}^{K} h_k(a_{k1}+1) \sum_{k=1}^{K} l_k(a_{k2}+1) - \sum_{k=1}^{K} h_k a_{k2} \sum_{k=1}^{K} l_k a_{k1}$. I use proof by induction to show that

$$Z(m) = \sum_{k=1}^{m} h_k(a_{k1}+1) \sum_{k=1}^{m} l_k(a_{k2}+1) - \sum_{k=1}^{m} h_k a_{k2} \sum_{k=1}^{m} l_k a_{k1} > 0, \quad \forall\, m \geq 1.$$

The following properties are employed: (1) as $\alpha_1 > \alpha_2 > ... > \alpha_K$, $\frac{h_1}{l_1} > \frac{h_2}{l_2} > ... > \frac{h_K}{l_K}$; (2) $a_{k1} + a_{k2} + 1 = \delta_k\varepsilon - \gamma_k\theta_h + 1 > 0\ \forall\, k$.

First, it is straightforward to show that $Z(1) = h_1 l_1(a_{11}+a_{12}+1) > 0$. Second, suppose $Z(m-1) > 0$. It needs to prove that $Z(m) > 0$. Note that

$$\begin{aligned} Z(m) = & [h_m(a_{m1}+1) + \sum_{k=1}^{m-1} h_k(a_{k1}+1)][l_m(a_{m2}+1) + \sum_{k=1}^{m-1} l_k(a_{k2}+1)] \\ & - [h_m a_{m2} + \sum_{k=1}^{m-1} h_k a_{k2}][l_m a_{m1} + \sum_{k=1}^{m-1} l_k a_{k1}] \\ > & h_m l_m(a_{m1}+a_{m2}+1) + \sum_{k=1}^{m-1} l_k h_m(a_{m1}a_{k2} - a_{m2}a_{k1} + a_{m1} + a_{k2} + 1) \\ & + \sum_{k=1}^{m-1} l_m h_k(a_{m2}a_{k1} - a_{m1}a_{k2} + a_{m2} + a_{k1} + 1) \\ > & \sum_{k=1}^{m-1} l_k h_m(a_{m1} + a_{m2} + a_{k1} + a_{k2} + 2) > 0 \end{aligned}$$

where the first inequality comes from the assumption that $Z(m-1) > 0$. The second inequality uses the facts that $l_k h_m < l_m h_k$ and $a_{m2}a_{k1} - a_{m1}a_{k2} + a_{m2} + a_{k1} + 1 > 0 \; \forall \; k < m$.[24] Therefore, $\det(\mathbf{I} - \mathbf{\Phi A}) > 0$.

Then, the change in skill premium can be related to the exogenous changes in iceberg costs $\hat{\tau}_{ij,k}$ in the form

$$\hat{w}_{i,h} - \hat{w}_{i,l} = -b_{i,1} \sum_k h_{i,k} \sum_{j \neq i} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{ij,k} + b_{i,2} \sum_k l_{i,k} \sum_{j \neq i} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{ij,k} + \nu(\{\hat{\psi}_{i,k}\}) \quad \text{(B.5)}$$

where $b_{i,1} = \frac{\varepsilon \sum_k l_{i,k}(\delta_{i,k}\varepsilon - \gamma_{ii,k}+1)}{\det(\mathbf{I}-\mathbf{\Phi A})} > 0, b_{i,2} = \frac{\varepsilon \sum_k h_{i,k}(\delta_{i,k}\varepsilon - \gamma_{ii,k}+1)}{\det(\mathbf{I}-\mathbf{\Phi A})} > 0$ and $\nu(\{\hat{\psi}_{i,k}\})$ is the residual term capturing the effect of productivity shocks $\{\hat{\psi}_{i,k}\}_{k=1,\ldots,K}$.

Log-linearizing equation (3.1) obtains

$$\hat{\pi}_{i,h} = \frac{\kappa}{1-\nu}(1-\pi_{i,h})(\hat{w}_{i,h} - \hat{w}_{i,l}) \quad \text{(B.6)}$$

Substituting equation (B.5) into (B.6) obtains

$$\hat{\pi}_{i,h} = -c_{i,1} \sum_k h_{i,k} \sum_{j \neq i} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{ij,k} + c_{i,2} \sum_k l_{i,k} \sum_{j \neq i} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{ij,k} + \tilde{\nu}(\{\hat{\psi}_{i,k}\}) \quad \text{(B.7)}$$

where $c_{i,1} = \frac{\kappa}{1-\nu}(1-\pi_{i,h})b_{i,1} > 0$ and $c_{i,2} = \frac{\kappa}{1-\nu}(1-\pi_{i,h})b_{i,2} > 0$.

B.2 Export Demand Shocks: From National to Local

This section derives a reduced form relationship mapping sectoral demand shocks from the ROW to changes in school enrollment of local economies in China. In particular, the iceberg cost of exporting good k from region i in China to region j in the ROW is assumed to take the form $\tau_{ij,k} = \tau_{j,k}\tilde{\tau}_{ij,k}$, where $\tau_{j,k}$ captures the common costs incurred by all the exporters in China, and $\tilde{\tau}_{ij,k}$ captures the idiosyncratic costs applying to prefecture i. Also, I assume $\hat{\tau}_{ij,k} = 0$ if $j \in China$, that is the iceberg costs between China's prefectures are constant. Then Equation $(B.7)$ can be rewritten as

$$\hat{\pi}_{i,h} = -c_{i,1} \sum_k h_{i,k} \sum_{j \in ROW} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{j,k} + c_{i,2} \sum_k l_{i,k} \sum_{j \in ROW} \gamma_{ij,k}(1-\lambda_{ij,k})\hat{\tau}_{j,k} + \tilde{\nu}(\hat{\psi}_{i,k}, \hat{\tilde{\tau}}_{ij,k}) \quad \text{(B.8)}$$

I assume $\lambda_{ij,k} \approx 0$, i.e., each prefecture in China has a small market share in region j of the ROW. Note that by definition, $h_{i,k} = H_{i,k}/H_i$, $l_{i,k} = L_{i,k}/L_i$ and $\gamma_{ij,k} = X_{ij,k}/Y_{i,k}$, then Equation (B.8)

[24] Note that $a_{m2}a_{k1} - a_{m1}a_{k2} + a_{m2} + a_{k1} + 1 = \sigma_m\sigma_k\varepsilon^2(\alpha_k - \alpha_m) + \sigma_m\varepsilon\gamma_k(\alpha_m - \theta) + \sigma_k\varepsilon\gamma_m(\theta - \alpha_k) + \sigma_m\varepsilon(1 - \alpha_m) + \sigma_k\varepsilon\alpha_k - \gamma_m\theta - \gamma_k(1-\theta) + 1 > \sigma_m\sigma_k\varepsilon^2(\alpha_k - \alpha_m) + \sigma_m\varepsilon\gamma_k(1-\theta) + \sigma_k\varepsilon\gamma_m\theta - \gamma_m\theta - \gamma_k(1-\theta) + 1 > 0$.

can be rewritten as

$$\hat{\pi}_{i,h} \approx -c_{i,1} \sum_k \frac{H_{i,k}}{H_i Y_{i,k}} \sum_{j \in ROW} \rho_{ij,k} X_{CHj,k} \hat{\tau}_{j,k} + c_{i,2} \sum_k \frac{L_{i,k}}{L_i Y_{i,k}} \sum_{j \in ROW} \rho_{ij,k} X_{CHj,k} \hat{\tau}_{j,k} + \tilde{\nu}(\hat{\psi}_{i,k}, \hat{\tilde{\tau}}_{ij,k})$$

where $X_{CHj,k}$ is China's total exports of good k to region j in the ROW, and $\rho_{ij,k} = X_{ij,k}/X_{CHj,k}$ denotes prefecture i's share in China's exports of good k to region j in the ROW. Due to lack of data on regional exports and outputs by sectors, $\rho_{ij,k}$ is approximated by prefecture i's share of China's employment in sector k, $E_{i,k}/E_k$,[25] and $Y_{i,k}$ is approximated by prefecture i's employment in sector k, $E_{i,k}$. Then

$$\hat{\pi}_{i,h} \approx \tilde{c}_{i,1} \sum_k \frac{H_{i,k}}{E_{i,k}} \frac{E_{i,k}}{E_k} \frac{\Delta X_k}{H_i} - \tilde{c}_{i,2} \sum_k \frac{L_{i,k}}{E_{i,k}} \frac{E_{i,k}}{E_k} \frac{\Delta X_k}{L_i} + \tilde{\nu}(\hat{\psi}_{i,k}, \hat{\tilde{\tau}}_{ij,k}) \tag{B.9}$$

where $\tilde{c}_{i,1}, \tilde{c}_{i,2} > 0$ and $\Delta X_k = \sum_{j \in ROW} \Delta X_{CHj,k} \propto \sum_{j \in ROW} X_{CHj,k} \hat{\tau}_{j,k}$ denotes the change in national exports induced by $\{\hat{\tau}_{j,k}\}$. Based on Equation (B.9), high-skill and low-skill export shocks are defined as

$$\Delta Export_{it}^{HS} = \sum_k \frac{H_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta X_{kt}}{H_{i0}} \tag{B.10}$$

$$\Delta Export_{it}^{LS} = \sum_k \frac{L_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta X_{kt}}{L_{i0}} \tag{B.11}$$

From Equation $(B.10)$, the national export expansion of sector k, ΔX_k, is apportioned to prefecture i according to its share of national industry employment E_{ik0}/E_{k0} in the base period. The regional export expansion is attributed to high-skilled workers according to the sector's skill intensity, $\frac{H_{ik0}}{E_{ik0}}$, and normalized by the amount of high skilled labor H_{i0}. Therefore, $\Delta Export_{it}^{HS}$ can be interpreted as high skill demand shock induced by export demand shock. Similarly, $\Delta Export_{it}^{LS}$ can be interpreted as low skill demand shock induced by export demand shock.

C Data Appendix

C.1 Administration Division and Industrial Classifications

Consistent Prefectures

Each prefecture is assigned a four-digit code in the censuses. The codes can change over years, usually because urbanization changes rural prefectures ("Diqu") to urban prefectures ("Shi"), which does not necessarily mean re-demarcation. The changing boundaries of prefectures threatens

[25] A similar simplification is made in Autor, Dorn and Hanson (2013).

the consistency of the defined local economies over time. To address the problem, I map counties in 1990, 2000 and 2010 to prefectures where they belong to in 2005. By this construction, I have consistent 340 prefectures over years. The municipalities of Beijing, Chongqing, Shanghai and Tianjin are treated as prefectures in this paper.

Industrial Classifications

Data in this paper comes from multiple sources that adopt different industrial classifications. I map the data on employment, output, trade flows, tariffs, and so on to consistent 3-digit CSIC (1984) codes as follows: (1) ISIC data is converted to CSIC, using the concordance built by Dean and Lovely (2010), which cross-matches the 4-digit CSIC (2002) codes and ISIC Rev.3 codes. (2) Data at 4-digit CSIC (2002) is converted to 3-digit CSIC (1984), using the concordance built by the author.

C.2 Trade Data

Export Tariff and Import at 3-digit CSIC

Data on China's export tariffs imposed by destination countries for 4-digit ISIC Rev.3 industries are collected from the TRAINS Database. The tariff faced by the Chinese exporters in a 4-digit ISIC industry k during year t is computed according to

$$Tariff^X_{kt} = \sum_c \frac{Export_{China,c,k,t-1}}{Export_{China,k,t-1}} Tariff_{ckt}$$

where $Tariff^X_{ckt}$ denotes the tariff imposed by country c on goods of industry k during period t. The tariffs are weighted by the country's share in China's total exports of good k in the lag period, i.e. $\frac{Export_{China,c,k,t-1}}{Export_{China,k,t-1}}$, and then aggregated to the industry level. These weights are constructed using the trade flow data from three years previously. The export tariffs for 3-digit CSIC industries are calculated as the weighted average of the corresponding 4-digit ISIC tariffs.

Data on import tariffs imposed by China on 4-digit ISIC Rev.3 industries are collected from the TRAINS database. Import tariffs on 3-digit CSIC industries are computed as the weighted average of the associated 4-digit ISIC tariffs.

Imports of Intermediate and Capital Goods

From the TRAINS database, I extract the data on imports and import tariffs of 6-digit Harmonized System (HS) products classified as Intermediate and capital goods by UNCTAD Stages of Processing (SoP). I conduct the following steps to construct the measures $\Delta Import^{s,CI}_{kt}$ employed in the main text: (1) Using the concordance provided by UN WITS, the data are mapped to

4-digit ISIC Rev.3 industries, and then aggregated to the 3-digit CSIC level; (2) the fitted value of imports of intermediate and capital goods, $\widehat{Import}_{kt}^{CI}$, is obtained from the regression

$$\ln Import_{kt}^{CI} = \beta \ln(Tariff_{it}^{M,CI}) + \gamma_k + \phi_t + \mu_{kt} \; ;$$

(3) The intermediate and capital goods import shocks are constructed as

$$\Delta Import_{it}^{LS,CI} = \sum_k \frac{L_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta \widehat{Import}_{kt}^{CI}}{L_{i0}} \quad \text{and} \quad \Delta Import_{it}^{HS,CI} = \sum_k \frac{H_{ik0}}{E_{ik0}} \frac{E_{ik0}}{E_{k0}} \frac{\Delta \widehat{Import}_{kt}^{CI}}{H_{i0}}.$$

C.3 Employment and Output Data at 2-digit CSIC codes

This section describes the sources of data used in section 7. The 2-digit CSIC manufacturing industry employment data and the local total employment data for each county are collected from the population censuses. The 1990 employment data, which covers China's entire population, is from the University of Michigan's China Data Center. Data for year 2000 and for 2010 is from various books of Population Census Data Assembly published by the provincial statistics bureaux,[26] which cover 10% of the population. These county-level data are then aggregated the to prefecture level using the concordance described in Appendix C.1.

There are 27 manufacturing industries, which are consistently defined across census years. For the purpose of analysis, I classify these industries into three groups according to the skill-intensity. To be specific, the industries are ranked by the share of college educated workers in their employment in 1990. Industries belonging to the bottom 33% , middle 33%, and top 33% are considered as low-, medium- and high-skill groups, respectively. Table C.1 lists the industries by skill group.

The data on industry output is from the Chinese Industrial Annual Survey 2000 and 2009. This data contains detailed micro-data for all state-owned firms and non-state firms with revenues above 5 million RMB (approximately US$800,000). These firms account for around 90% of the value of manufacturing outputs. Brandt, Biesebroeck and Zhang (2012) provide a detailed description of the data and show that the data can be aggregated almost perfectly to reflect the data reported in the Chinese Statistical Yearbooks.

[26] The data for province Shangdong is not available for 2010.

Table C.1: Skill Intensities of 2-digit Manufacturing Industries

Low-skill Industries	**Medium-skill Industries**
Food Processing and Production (13-14)	Beverage (15)
Garments, Footwear and Related Products (18)	Tobacco (16)
Leather, Furs, Down and Related Products (19)	Textiles (17)
Furniture Manufacturing (21)	Timber Processing and Related Products (20)
Cultural, Educational and Sporting Goods (24)	Pulp, Paper, Paper Products (22)
Plastic Products (30)	Printing and Publishing (23)
Nonmetal Mineral Products (31)	Petroleum Processing and Coking (25)
Metal Products (34)	Raw Chemical Materials and Chemical Products (26)
Manufacturing, n.e.c. (42)	Rubber Products (29)
High-skill Industries	
Medical and Pharmaceutical Products (27)	
Chemical Fiber (28)	
Smelting and Pressing of Ferrous Metals (32)	
Smelting and Pressing of Nonferrous Metals (33)	
Machinery (35-36)	
Transport Equipment (37)	
Electric Equipment and Machinery (39)	
Electronic and Telecommunications Equipment (40)	
Instruments, Meters, Cultural and Office Machinery (41)	

Notes: 2-digit CSIC codes in the parentheses.

D Robustness

D.1 Migration Pattern and Export Shocks

This section examines the effects of regional export shocks on the migration flows using data from the 2000 and 2005 population censuses on the prefecture of residence five years previously. The sample is restricted to individuals of prime working age (those aged 23 to 55). The immigration and emigration rates of prefecture i are defined as

$$IMR_{it}^{s} = IM_{it}^{s}/(IM_{it}^{s} + Pop_{it-1}^{s}) \quad \text{and} \quad EMR_{it}^{s} = EM_{it}^{s}/Pop_{it-1}^{s}$$

where IM_{it}^{s} and EM_{it}^{s} denote, respectively, the total immigrants and emigrants of prefecture i with education level s during the past five years, and Pop_{it-1}^{s} is the total population of education level s in prefecture i five years ago.

Columns (1) of Table D.1 relates the immigration pattern of unskilled workers to export shocks by estimating the following regression:

$$\Delta IMR_{it}^{LS} = \sum_{s\in\{LS,HS\}} \theta_s \Delta Export_{it}^{s} + \phi_p + \varepsilon_{it} \tag{D.1}$$

where ΔIMR_{it}^{LS} is the change in immigration rate of workers with high school education or lower between 2000 and 2005, and ϕ_p denotes the province dummy. Low-skill export shocks are found to attract low-skilled immigrants, whereas high-skill export shocks deter them. The estimates imply that a \$1000 low-skill export expansion increases ΔIMR_{it}^{LS} by 2.3 percentage points, and a \$1000 low-skill export expansion decreases ΔIMR_{it}^{LS} by 0.2 percentage points. Column (2) re-estimates Equation (D.1) but changes the dependent variable to ΔIMR_{it}^{HS}, i.e., the change in the immigration rate of workers with college education or above between 2000 and 2005. The estimated coefficients θ_k are close to zero and statistically insignificant, suggesting that export shocks have little effect on the immigration flow of skilled workers. Columns (3) and (4) show the effects of export shocks on the emigration rates of workers with different educational attainment. Low-skill export shocks reduce the out-migration of workers with high school education or lower, and induce more emigration of workers with college education or above. However, the effects of high-skill export shocks are found to be insignificant regardless of the type of worker.

Column (5) replaces the dependent variable with $\Delta \frac{IM_{it}^{LS}}{EM_{it}^{LS}}$ (i.e., the change in the ratio of inflows to outflows of low-skilled workers) to study the effects on net flows of low-skilled workers. Consistent with the finding in Columns (1) and (3), low-skill export shock induces more low-skilled immigrants relative to emigrants, and high-skill export shock lowers the ratio. Column (6) shows that export shocks have no significant effect on the net migration flow of skilled workers. Conclusively, low-skill export expansion lowers the average education of immigrants and increases the average education of emigrants. The converse is true in the case of high-skill export expansion. Export shocks are found to alter the composition of migrant workers mainly through their effect on the migration pattern of low-skilled workers.

D.2 Effects on Export Demand Shocks on School Enrollment of Local Youths

Large inflows of immigrants could reduce the responsiveness of non-migrant education to local export shocks. To investigate this possibility, I look at data from the 2000 and 2005 population censuses which record the prefecture of residence 5 years previously. Columns (1) of Table D.2 examines the effects of export shocks on immigrant share of the high school age population ($\Delta\frac{IM}{Pop}$). The estimated coefficients of $\Delta Export^s$ are small and insignificantly different from zero. Columns (2) and (3) present the effects of export shocks on the high school enrollment rate for the baseline sample (immigrants and locals) and non-migrant sample, respectively. If the negative (positive) educational impact of low-skill (high-skill) export shock is purely explained by the inflows of low skilled (high skilled) young workers, the estimate of β^{LS} (β^{HS}) is expected to diminish significantly when the sample is restricted to non-migrants. However, the estimated coefficients of the two samples are found to be statistically similar. Given the evidence from Columns (1)–(3), export shocks are unlikely to change the high school enrollment rate by altering the composition of school age population alone.

Columns (4)–(6) report analyses analogous to Columns (1)–(3), but focus on the population aged 19 to 22. Again, export shocks are found to have little effect on the inflow of college age immigrants. The effect of low-skill (high-skill) export shock is still estimated to be significantly negative (positive) when the sample is restricted to non-migrants, albeit smaller in magnitude than that of the baseline sample.

D.3 Heterogeneous Reponses to Export Shocks of Different Demographic Groups

In Table D.3, I investigate the heterogeneous responses of different demographic groups to export shocks, using the specification of Column (4) in Table 2. Columns (1) and (2) show the effects of export shocks on school enrollment by gender. The estimates are statistically similar for the two genders and remain statistically significant at conventional levels for all outcomes, with the exception of boys' high school enrollment in the case high-skill export shocks, where the estimate is marginally insignificant, with a p-value of 0.12.

Columns (3) and (4) present the regression results for the samples of young people with urban and rural Hukou, respectively. Regardless of the outcome variables and samples, the estimates retain the expected signs and significance. In addition, the estimated effects of export shocks on high school enrollment are quantitatively similar across samples. In contrast, export shocks are found to have larger effects on college enrollment in magnitude in the urban sample than in the rural sample. In particular, the estimate of the high-skill export shock is statistically larger for young people with urban Hukou, which may be explained by urban residences proximity to colleges.

D.4 Dropping One Province/Two Provinces at a Time

To test whether the findings are driven by a particular geographic region, I estimate the specification of Column (4) in Table 2, and drop one province or two provinces at a time. Panel A of Table D.4 shows the results for dropping one province at a time. For the sample of young people aged 16 to 18, the estimates of β^{LS} range from -0.050 to -0.026, and the estimates of β^{HS} range from 0.005 to 0.007. For the sample of young people aged 19 to 22, the estimates of β^{LS} range from -0.034 to -0.030, and the estimates of β^{HS} range from 0.006 to 0.008. All these estimates are significant at the conventional level. Panel B presents the results for dropping two provinces at a time. The estimates are not sensitive to the exclusion of any combination of two provinces.

D.5 Children under Compulsory Schooling

In principle, if the law of compulsory schooling is perfectly enforced, then primary and junior secondary education are not relevant margins for education choices in this study. However, as is discussed in Section 5, although it is improving over time, the enforcement of compulsory schooling in China is imperfect, especially for children aged 13 to 15. Table D.5 presents the regression results when the sample is restricted to the children aged between 7 to 15. Columns (1) to (3) show that export shocks have no effect on the school enrollment of primary school age children. Columns (4) to (6) find small but significant educational impacts of high-skill export shock for the age group 13 to 15. The estimates imply that a \$1000 high-skill export shock raises middle school enrollment by 0.2 to 0.4 percentage point. Column (5) also detects a significantly negative effect of low-skill export shock on middle school enrollment, with a \$1000 exposure lowering it by 0.6 percentage point. It is found in the unreported results that the significant effects of export shocks on school enrollment for the 13–15 age group are mainly driven by fifteen-year-olds. As is shown in Figure 2, the enforcement of compulsory schooling is weakest for this marginal age group.

D.6 Other Market Outcomes

Table D.6 re-estimates the specification in Column (4) of Table 2, with the dependent variable replaced by different variables related to market outcomes. Columns (1) and (4) report the effect of export expansion on market employment. The estimates resemble those in Table 2, but with flipped signs. As is shown in Columns (2) and (5), exports shocks are estimated to have no effect on home production. This result is in contrast to the findings of Edmonds and Pavcnik (2005) and Edmonds, Pavcnik and Topalova (2010) that trade affects children's engagement in domestic work through the income effect. In addition, Columns (3) and (6) show that low-skill export shocks decrease the unemployment rate of young people aged 16 to 22, but the effects of high-skill shocks are statistically insignificant. This is consistent with the priori that low-skill export expansion provides more jobs for young people who drop out of school, whereas the job opportunities generated by high-skill shocks are not relevant to them.

D.7 Disaggregated Export Demand Shocks

In this section, I construct the export shock $Export^s$ at three levels of skill intensity, where $s \in \{LS, MS, HS\}$, following a strategy similar to that described in Section 5.4. Specifically,

$$\Delta Export_{it}^{LS} = \sum_k \frac{L_{ik0}}{L_{i0}} \frac{\Delta \widehat{Export}_{kt}}{E_{k0}}, \; \Delta Export_{it}^{MS} = \sum_k \frac{M_{ik0}}{M_{i0}} \frac{\Delta \widehat{Export}_{kt}}{E_{k0}},$$

$$\text{and} \quad \Delta Export_{it}^{HS} = \sum_k \frac{H_{ik0}}{H_{i0}} \frac{\Delta \widehat{Export}_{kt}}{E_{k0}}.$$

where the low-skilled workers (L) are those with middle school education or lower, the medium-skilled workers (M) are those with some high school education, and the high skilled workers (H) are those with some college education.

Table D.7 presents the regression results using modified export shocks. Columns (1) and (3) show that low-skill shock has an adverse effect on high school and college enrollment, whereas the effect of high-skill shock is estimated to be significantly positive. It is worth noting that $\Delta Export_{it}^{MS}$ has two offsetting effects on high school and college enrollments. One the one hand, positive medium-skill shocks increase the demand for high school educated workers. On the other hand, positive medium-skill shocks discourage young people from pursuing college education. As secondary education is a prerequisite for college, the first channel encourages high school and college enrollments, but the second channel tends to depress both. As is shown in Columns (1) and (3), the effects of medium-skill shock are found to be insignificant. Columns (2) and (4) augment the model with the controls PLI and PHI and the estimates change little. Lastly, Columns (3) and (6) control the prefecture dummies. The effects of $\Delta Export_{it}^{LS}$ are less precisely estimated. Specifically, the effect of low-skill shock on high school enrollment becomes marginal insignificant, with a p-value of 0.14. In addition, a significantly negative effect of medium-skill shock is detected for the 16-18 age group.

D.8 Change in Skill Supply and Industry Specialization: Different Measures

Table D.8 repeats the analysis in Table 5, but replaces $\Delta HighSch.Enroll_{it-1}$ with $\Delta HighSch.Share_{it-1}$ (i.e., change in the share of population with some high school education over the period 1990 to 2000), and replaces $\Delta College.Enroll_{it-1}$ with $\Delta College.Share_{it-1}$ (i.e., change in the share of the population with some college education over the period 1990 to 2000). Unlike school enrollment, the share of workers with different educational attainment is a stock variable measuring skill supply.

The findings in Table D.8 are consistent with those in Table 5, regardless of the measures of industry share. The 2SLS estimates in Column (2) suggest that a 10 percentage point increase in $CollegeShare_{it-1}$ raises a high-skill industry's share of total employment in the manufacturing sector by 3.37 percentage points, and reduces a low-skill industry's share of total employment in the manufacturing sector by 3.79 percentage points.

Table D.1: Migration and Export Shocks

	ΔIMR^{LS} (1)	ΔIMR^{HS} (2)	ΔEMR^{LS} (3)	ΔEMR^{HS} (4)	$\Delta \frac{IM^{LS}}{EM^{LS}}$ (5)	$\Delta \frac{IM^{HS}}{EM^{HS}}$ (6)
$\Delta Export^{LS}$	0.023***	-0.001	-0.005**	0.008**	24.153**	0.357
	(0.005)	(0.002)	(0.002)	(0.003)	(10.008)	(0.361)
$\Delta Export^{HS}$	-0.002*	-0.001	0.002	0.000	-2.433*	-0.029
	(0.001)	(0.001)	(0.001)	(0.002)	(1.321)	(0.039)
Province	Y	Y	Y	Y	Y	Y
N	340	340	340	340	340	340
R^2	0.471	0.573	0.626	0.485	0.535	0.614

Notes: Robust standard errors in the parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table D.2: Changes in Share of Immigrants, Change in School Enrollment and Export Shocks: Different Samples by Migration Status

	Age 16-18			Age 19-22		
	$\Delta \frac{IM}{Pop}$ All (1)	$\Delta Enroll$ All (2)	$\Delta Enroll$ Non-migrants (3)	$\Delta \frac{IM}{Pop}$ All (4)	$\Delta Enroll$ All (5)	$\Delta Enroll$ Non-migrants (6)
$\Delta Export^{LS}$	0.017	-0.029**	-0.019*	0.007	-0.027***	-0.013*
	(0.011)	(0.012)	(0.011)	(0.009)	(0.006)	(0.008)
$\Delta Export^{HS}$	-0.001	0.004**	0.006***	0.002	0.006***	0.004**
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)
Province	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y
PHI and PLI	Y	Y	Y	Y	Y	Y
N	340	340	340	340	340	340
R^2	0.594	0.694	0.633	0.718	0.662	0.703

Notes: All regressions are weighted by the start-of-the-period prefecture's age group population. Controls include change in average age, change in sex ratio, change in share of Han ethnic group, change in share of population with urban Hukou, change in log fiscal expenditure on education, and change in log GDP per capita. Initial conditions include the start of period school enrollment rate and log GDP per capita. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table D.3: Changes in School Enrollment and Export Shocks: by Samples

	Boy (1)	Girl (2)	Urban (3)	Rural (4)
Panel A: Age 16-18				
$\Delta Export^{LS}$	-0.029***	-0.041***	-0.027*	-0.036***
	(0.009)	(0.012)	(0.014)	(0.011)
$\Delta Export^{HS}$	0.004	0.008***	0.008***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Province×Year	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y
PHI and PLI	Y	Y	Y	Y
N	673	673	665	672
R^2	0.640	0.716	0.729	0.707
Panel B: Age 19-22				
$\Delta Export^{LS}$	-0.029***	-0.030***	-0.028**	-0.015***
	(0.006)	(0.005)	(0.011)	(0.004)
$\Delta Export^{HS}$	0.009**	0.005*	0.018***	0.005***
	(0.003)	(0.003)	(0.005)	(0.001)
Province×Year	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y
PHI and PLI	Y	Y	Y	Y
N	673	673	673	673
R^2	0.734	0.715	0.770	0.769

Notes: All regressions are weighted by the start-of-the-period prefecture's age group population. Controls include change in average age, change in sex ratio, change in share of Han ethnic group, change in share of population with urban Hukou, change in log fiscal expenditure on education, and change in log GDP per capita. Initial conditions include the start of period school enrollment rate and log GDP per capita. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table D.4: Dropping One Province/Two Provinces at a Time

	Age 16-18		Age 19-22	
	min($\hat{\beta}$)	max($\hat{\beta}$)	min($\hat{\beta}$)	max($\hat{\beta}$)
	(1)	(2)	(3)	(4)
Panel A: Dropping one province at a time				
$\Delta Export^{LS}$	-0.050**	-0.026***	-0.034**	-0.030***
	(0.020)	(0.008)	(0.013)	(0.005)
$\Delta Export^{HS}$	0.005**	0.007***	0.006***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Panel B: Dropping two provinces at a time				
$\Delta Export^{LS}$	-0.060***	-0.024***	-0.040***	-0.021*
	(0.019)	(0.007)	(0.013)	(0.012)
$\Delta Export^{HS}$	0.004**	0.009***	0.006**	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)

Notes: All regressions are weighted by the start-of-the-period prefecture's share of the cohort population. All regressions include the controls in the specification (4) of Table 2. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table D.5: Change of School Enrollment and Export Shocks:
Ages under Compulsory Schooling

	Age 7-12			Age 13-15		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Export^{LS}$	0.001	0.001	0.001	-0.005	-0.006*	-0.012
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.008)
$\Delta Export^{HS}$	-0.000	-0.000	-0.000	0.003***	0.002***	0.004*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Province	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y
PHI and PLI		Y			Y	
Prefecture			Y			Y
N	673	673	673	673	673	673
R^2	0.956	0.956	0.995	0.858	0.859	0.980

Notes: All regressions are weighted by the start-of-the-period prefecture's age group population. Controls include change in average age, change in sex ratio, change in share of Han ethnic group, change in share of population with urban Hukou, change in log fiscal expenditure on education, and change in log GDP per capita. Initial conditions include the start of period school enrollment rate and log GDP per capita. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table D.6: Changes of Market Employment, Home Production, Unemployment Rate and Export Shocks

	Age 16-18			Age 19-22		
	$\Delta Market$ $Empl.$	$\Delta Home$ $Prod.$	$\Delta Unemp.$ $Rate$	$\Delta Market$ $Empl.$	$\Delta Home$ $Prod.$	$\Delta Unemp.$ $Rate$
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Export^{LS}$	0.036***	0.001	-0.011*	0.039***	-0.001	-0.012***
	(0.009)	(0.002)	(0.006)	(0.004)	(0.001)	(0.003)
$\Delta Export^{HS}$	-0.006**	0.000	0.002	-0.009***	0.001	0.002
	(0.002)	(0.000)	(0.003)	(0.002)	(0.000)	(0.001)
Province	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y
PHI and PLI	Y	Y	Y	Y	Y	Y
N	673	673	673	673	673	673
R^2	0.713	0.279	0.545	0.781	0.300	0.635

Notes: Notes: All regressions are weighted by the start-of-the-period prefecture's age group population. Controls include change in average age, change in sex ratio, change in share of Han ethnic group, change in share of population with urban Hukou, change in log fiscal expenditure on education, and change in log GDP per capita. Initial conditions include the start of period school enrollment rate and log GDP per capita. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

Table D.7: Changes in School Enrollment, Export Shocks and Import Shocks: Disaggregated Education Groups

	Age 16-18			Age 19-22		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Export^{LS}$	-0.019**	-0.025***	-0.036	-0.017***	-0.027***	-0.023*
	(0.007)	(0.009)	(0.023)	(0.004)	(0.005)	(0.012)
$\Delta Export^{MS}$	-0.005	-0.007	-0.022*	-0.004	-0.004	-0.019
	(0.007)	(0.007)	(0.012)	(0.006)	(0.006)	(0.012)
$\Delta Export^{HS}$	0.007***	0.006**	0.011**	0.011***	0.007***	0.012**
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)
Province	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Initial Conditions	Y	Y	Y	Y	Y	Y
PHI and PLI		Y			Y	
Prefecture			Y			Y
N	673	673	673	673	673	673
R^2	0.682	0.693	0.925	0.696	0.762	0.920

Notes: All regressions are weighted by the start-of-the-period prefecture's age group population. Controls include change in average age, change in sex ratio, change in share of Han ethnic group, change in share of population with urban Hukou, change in log fiscal expenditure on education, and change in log GDP per capita. Initial conditions include the start of period school enrollment rate and log GDP per capita. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1

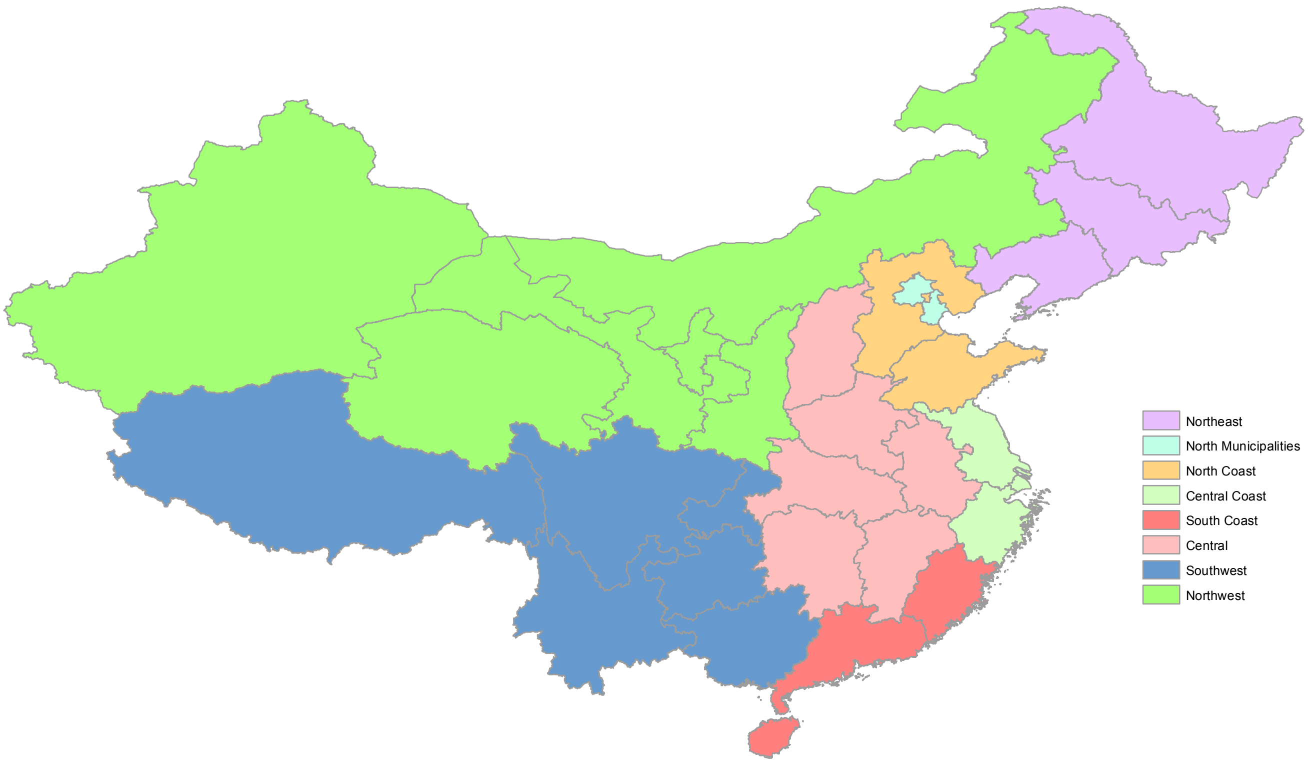
Table D.8: Changes in Skill Supply and Change in Industry Specialization: Different Measures

	$\Delta Share^M$				$\Delta Share$	
	Employment		Output		Employment	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
$LS \times \Delta HighSch.Share_{t-1}$	-0.005	0.253**	-0.005	0.322*	-0.002	0.134**
	(0.021)	(0.099)	(0.033)	(0.187)	(0.005)	(0.061)
$MS \times \Delta HighSch.Share_{t-1}$	0.013	-0.040	0.005	-0.196	0.002	0.024
	(0.022)	(0.061)	(0.031)	(0.214)	(0.003)	(0.016)
$HS \times \Delta HighSch.Share_{t-1}$	-0.009	-0.214**	0.000	-0.111	0.000	-0.060*
	(0.016)	(0.089)	(0.032)	(0.212)	(0.004)	(0.033)
$LS \times \Delta College.Share_{t-1}$	-0.058	-0.379***	-0.055	-0.388**	-0.017	-0.245***
	(0.037)	(0.140)	(0.049)	(0.156)	(0.013)	(0.087)
$MS \times \Delta College.Share_{t-1}$	-0.006	0.042	0.010	0.075	-0.010	-0.074***
	(0.033)	(0.079)	(0.045)	(0.191)	(0.006)	(0.028)
$HS \times \Delta College.Share_{t-1}$	0.064**	0.337***	0.055	0.313*	0.003	0.087*
	(0.028)	(0.125)	(0.050)	(0.175)	(0.007)	(0.051)
$\Delta ShareEmp^M_{t-1}$	Y	Y	Y	Y		
$\Delta ShareEmp_{t-1}$					Y	Y
Province×Ind	Y	Y	Y	Y	Y	Y
N	8,721	8,721	9,180	9,180	8,721	8,721

Notes: All regressions control for the start-of-the-period industry employment/output share. Standard errors are clustered at the prefecture level. *** p<0.01, ** p<0.05, * p<0.1

E Calibration

Figure 6: Regions in China



Note: Regions include Northeast (provinces Heilongjiang, Jilin and Liaoning), North Municipalities (provinces Beijing and Tianjin), North Coast (provinces Hebei and Shangdong), Central Coast (provinces Shanghai, Jiangsu and Zhejiang), South Coast (provinces Guangdong, Fujian and Hainan), Central (provinces Henan, Shanxi, Anhui, Jiangxi, Hubei and Hunan), Southwest (provinces Guangxi, Chongqing, Sichuan, Guizhou, Yunnan and Tibet), and Northwest (provinces Inner Mongolia, Shannxi, Gansu, Qinghai, Ningxia and Xinjiang).

Table E.1: Calibration and Data Sources

Variables and Parameters	Data
Income(Y_i), bilateral tradeflows($\lambda_{ij,k}$) sectoral output($Y_{i,k}$), & consumption share(β_k)	China Regional IO Table, 2007 & WIOD, 2007
Employment share of skilled and unskilled labor($h_{i,k}$ and $l_{i,k}$)	China 2005 Mini Census & WIOD SEA, 2007
Income share of skilled workers(α_k)	China 2005 Mini Census
School enrollment rate($\pi_{i,s}$)	China 2005 Mini Census Barro and Lee, 2005
Trade elasticity ($\varepsilon = 4.14$)	Simonovska and Waugh(2014)
Skill distribution parameter ($\kappa = 3.36$)	China 2005 Mini Census

Table E.2: Calibrated α_k and β_k

Sector	α_k	β_k
Agriculture, Hunting, Forestry and Fishing	0.01	0.06
Mining and Quarrying	0.16	0.05
Food, Beverages and Tobacco	0.14	0.05
Textiles, Apparels, Footwear and Leather Products	0.06	0.04
Wood and Products of Wood and Cork	0.04	0.01
Pulp, Paper, Paper, Printing and Publishing	0.14	0.02
Chemicals and Chemical Products	0.24	0.11
Non-Metallic Products	0.07	0.03
Basic Metals and Fabricated Metal	0.13	0.10
Machinery, n.e.c.	0.24	0.06
Transportation Equipment	0.24	0.05
Electrical and Optical Equipment	0.34	0.07
Manufacturing, Nec	0.06	0.02
Other Non-manufacturing	0.35	0.34