QUEEN'S UNIVERSITY

Wage Impact of Multilateral Trade Liberalization with Labor Adjustments

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Abstract

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This paper extends the Melitz (2003) model of trade to account for heterogeneity of workers across different productivity levels. We further extend the model to allow for mobility of workers both across regions and between skill levels. This added level of richness allows us to examine the wage outcomes of workers in response to trade liberalization as a function of cost of access to mobility. The model generates predictions regarding China's transition period into the WTO. We examined our hypothesis using data for both urban and rural regions, showing that not only is there a statistical and economic significant relationship between education access and wages, it is also a driving force behind the wage gap between urban-rural workers.

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Contents

1 Introduction

1.1 Issue and Motivation

This paper extends the Melitz (2003) model of trade to account for heterogeneity of workers across different productivity levels. We further extend the model to allow for mobility of workers both across regions and between skill levels. This added level of richness allows us to examine the wage outcomes of workers in response to trade liberalization as a function of cost of access to mobility. The model generates predictions regarding China's transition period into the WTO. We examined our hypothesis using data for both urban and rural regions, showing that not only is there a statistical and economic significant relationship between education access and wages, it is also a driving force behind the wage gap between urban-rural workers.

China is a particularly attractive subject for this research due to the magnitude and speed of its liberalization process and the dominant role trade has played in its modernization in recent years. Furthermore, China has a large trade exposure gap inherent in its rural-urban split due to the heavy industrialization of its cities in the 80s and 90s but relatively poor and underdeveloped rural regions. Similarly, there is also a large education gap along the same lines, with little participation in higher education in poorer country sides. This provides an excellent set up to study a model where geographic and skill based mobility is isolated using the rural and urban divide. Furthermore, China is particularly interesting due to the behavior of its wage distribution over the years: Despite being a large and relatively labor abundant economy, it suffered growing skill based wage inequalities in contrary to traditional trade models. On the other hand, we also see in recent years that the trend has been aggressively declining- especially across the rural urban divide. Both the direction of the change and the rate of adjustment suggest that it is not just the equilibrium correction process predicted by most trade models and that some other factors are at play.

The balance of the paper is structured as thus: In the next section I take a look at related literature in both international and labor economics. Chapter 2 outlines the theoretical framework for the model, breaking down its derivation from the basic two factor model with no frictions or mobility to a less restrictive two period model with labor adjustments and imperfect information. Here I also discuss the theoretical findings from the perspective of wage income and inequality. Chapter 3 details the data and methodologies of the empirical work used to examine the predictions of the model. Chapter 4 discusses the results of the empirical work and conduct Several robustness checks of the main estimation result. Chapter 5 concludes.

1.2 Related Literature

Since this paper straddles the border between international economics and labor economics, we will approach our review of past works from both perspectives. While the topic of wage or welfare inequality has been studied by an enormous body of work, and the topic of labor mobility is a centerpiece in a great deal of papers, most research is focused on geographic mobility or movements between industries and firms. Less attention has been paid to the prospect that workers can move between skill categories, and those few that studies education outcomes focus primarily on the education income gap itself rather than the cost of education as a contributor to on eventual wage distributions. Thus, the following review focuses on models that addresses these topics directly and is the basis of my theoretical framework.

1.2.1 Trade Theory

Distributional outcomes for workers in the classical international economic models generally boils down to variations on the specific factors model by Samuelson or the factor proportional model by Heckscher-Ohlin. In the former, as trade liberalizes, factors employed in the export oriented sector benefits while factors employed in the import competing industry suffers wage declines. While this model provides one explanation for the wage divide between labor groups, it implies a perfectly rigid labor market with zero mobility across regions. These restrictions apply more easily to generally immobile factors such as land or certain types of equipment, but they are ill suited to explain labor adjustments in vast majority of the scenarios.

The factor proportional model relaxes these restrictions and instead supposes that competitive advantage and thus wages is driven by the relative abundance of factor endowment and the relative intensity by which these factors are employed. These models typically conclude that factors that are more intensively employed by the export industries tend to have higher wages compared to factors that are more intensively employed by import industries. However, little distinction is made between the types of mobility and the level of analysis tend to stay at the industry(and national) level, which ignores the variation in wages across regions as well as across firms

More modern trade theories following Krugman(1980)'s seminal work focuses on firm level analysis and features heterogeneity from both the firm and worker's perspective. Melitz(2003) introduced a firm-differentiated trade model that provided an explanation for the general pattern of increased size and productivity of trading firms. However, he made no attempt to differentiate workers based on ability and focused primarily on general welfare measures. Helpman(2010) extended upon this work by looking at skill-differentiated workers from a matching perspective. In this model, workers are homogeneous until matched with a firm and draw a productivity measure upon employment. The firm then has the option to screen for higher worker productivity. He finds that under this model, the unemployment rate is decreasing and wages are increasing in worker ability. Additionally, since more productive firms in the export sector has more resources to screen, they tend to employ more productive workers. From this he notes that inequality increases as a function of variance of skill distribution.

In a further analysis of labor rigidities Helpman and Isthoki(2015) notes that in the long term, welfare gains from trade liberalization do not depend on labor market frictions. On the other hand, in the short run, there are distributional effects based on the productivity of the firm. In particular, workers who are employed with high productivity firms have higher wages and better job security than workers who are employed in low productivity (and thus non-traded firms). Combined with his earlier work, we can see that skill disparity has a compounding effect on welfare outcomes from two distinct sources.

Other works, such as those by Artuc, Chaudhuri and Mclaren(2007) explored in depth the worker's decision when faced with mobility costs. Simulating standard trade model with labor mobility cost, it focused on analyzing the impact of imperfect mobility of workers on the adjustment to a trade shock. It concluded that when mobility costs were low, welfare of workers rose even in the import competing sectors. More interestingly, in both high and low cost cases considered in the paper, the bulk of the labor movement occurred between the announcement date of tariff reduction and the enactment date. Thus, it suggests that merely studying the labor movements after the fact could be misleading.

Similarly, Kenan and Walker (2011) studied worker mobility decisions from a labor economics point of view. Using a fully specified behavior model, it maps out multiple decision incidents with multiple choices of locations for geographical mobility with variant costs. They showed that from the perspective of regional mobility, workers are essentially faced with a optimal matching problem with imperfect information. They concluded that mobility choices are motivated not only by regional differences in mean wage but also realized wage outcomes.

1.2.2 Empirical Studies

Due to the relative transparency of the parties involved and the ease of access to large quantities of microdata, a great deal of empirical work looks at the fallout of the North American Free Trade Agreement. For instance, Hanson (2005) looks at welfare outcomes in Mexico following their decade of liberalization between the 90s and the early 2000s. Using regional variations on exposure to FDI as a measure of trade exposure. He found that overall high exposure areas had a rightward shift in the income distribution over areas less exposed to trade. This amounted to as much as 8-12% difference in wage income between the two types of regions. Similarly, Hakobyan and Mclaren (2016) looks at wage changes in US regions as a result of NAFTA and focuses more closely on worker mobility. Their analysis controlled for regional differences in trade exposure as well as accounting for relative comparative advantage of individual industries when compared to Mexico. As a result, they found that limitations on geographic and between-industry mobility are significant and there are large redistributional effects of these mobility limitations but little aggregate welfare changes.

Outside of the North America, work mainly focuses on developing countries and the wage inequalities that develop as a result of expanded trade. Topalova (2007) and (2004) looked at Indian districts and their respective reactions to globalization to find the opposite of previous work in that both poverty rate and poverty gap increased in regions with more exposure and that geographic mobility is highly limited in these regions. Furthermore, she made special note of the divide between rural and urban regions in that Rural regions with high industrial exposures faces increased inequality but no significant impact on poverty reduction compared to urban areas. Kovak (2013) examined Brazil and found comparable declines in wages in regions that faced more severe tariff decreases - upwards of 4% decline in wages in areas with 10% more exposure to tariff reduction.

As such, there is no consensus on the distributional outcome of trade liberalization empirically. Furthermore, the impact of worker mobility appeared ambiguous both in terms of its direction of influence on outcomes and in the significance of its presence- especially in poorer developing countries. Taking a closer look at China specifically we find that Ianchovichina and Martin(2004) examined the WTO accession aftermath using a computable general equilibrium model. One result of their analysis is that under certain assumptions, unskilled wages increases along side an increase in all real non-agriculture wages. Noting that workers in urban centers and farmers who are able to engage in non-farm employment benefits from the trade liberalization. Their analysis on reduction of labor mobility in rural regions note that by abolishing policy related barriers to labor movement such as the Hukou system improves real returns to rural workers by 17% and causes a 3.8% decline in real urban wages. Similarly, increases in education access (such as reduction in school fees) would boost real wages of poorer and unskilled workers while at the same time mitigate the increase in skilled workers' wage as a result of WTO accession.

Using the same CGE model, Chen and Ravallion (2004) finds that there is little overall aggregate gains in poverty reduction and that the leadup period actually experiences increased poverty due to rapid rises in prices. Using National Bureau of Statistics of China's household data, it notes that 3/4 of rural and 1/10 of urban households experiences an income loss. Further, it notes that inequality increases as the richer gets rich and the poorer gets poorer. Specifically, the urban rich gains more than equivalent households in rural areas and that generally distributional outcomes shifts by areas. Most interestingly, the paper claim that the welfare gains is u-shaped with respect to income levels, implying that intermediate households (ie. the urban poor) experiences the least gains overall.

2 Theoretical Framework

2.1 Baseline Model

We start by introducing heterogeneity in the labor force in the form of two types of workers. Skilled workers, denoted by S, have higher productivity compared to unskilled workers, denoted as U. The workers have full mobility across firms and earn wages w_s and w_u respectively. For the sake of simplicity, we assume there are two representative households each supplying one type of labor. Firms can choose to hire any number of workers of each type, constrained only by the maximum labor supply L_s and L_u.

As in the Melitz model, firms compete monopolistically and produce a differentiated product indexed by their respective productivities ϕ. In all cases, we assume that there are no frictions in both labor and goods markets and that prices adjust to ensure market clearing.

2.1.1 Consumers' Problem

As in the Melitz model, consumers have a CES utility function and obey their budget constraints. They face the following optimization problem:

$$\underset{q(w)_{\omega\in\Omega}}{\text{Max}} \left(\int_{\omega\in\Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{2.1}$$

subject to:

$$\int_{\omega\in\Omega} q(\omega)p(\omega)d\omega \leq w_i L_i \tag{2.2}$$

where Ω is the set of all available goods, σ is the elasticity of substitution, $p(\omega)$ is the price of variety ω, w_i is the wage available to worker type i ($i \in u, s$) and L_i is her labor supply. Workers have homogeneous preferences and have access to the same goods market but have different labor supplies and may earn different wages.

Taking first order conditions and substituting in the definition of the price index we have the familiar individual demand functions for a type i worker:

$$q_i(\omega) = p(\omega)^{-\sigma} P^{\sigma-1} w_i L_i \tag{2.3}$$

$$\text{where} \quad P = \left(\int_{\omega \in \Omega} p(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}$$

We can then calculate aggregate demand for each good by summing up the individual demands for both consumer types:

$$q(\omega) \equiv \sum_{i \in u,s} q_i(\omega) = p(\omega)^{-\sigma} P^{\sigma-1} \sum_{i \in u,s} w_i L_i \tag{2.4}$$

2.1.2 Firms' Problems, In Autarky

With multiple factors of production, a firm's problem is somewhat different than the Melitz model. While the one-factor model can use a simple linear production technology, here, to ensure that the two factor model has similar properties as the original model, the production technology is modified to Cobb-Douglas. We impose that the exponents to sum to 1 so that with a fixed cost, the production function exhibits increasing returns to scale.

More importantly, slight changes has to be made to the way fixed cost is modeled. In the one factor model, fixed cost is deducted directly from the amount of labor used in the production of goods. However, since there are now two types of labor input and each firm has different demand for each type of labor, two distinct types of fixed cost can be imposed.The first type involves deducting the fixed cost directly from the labor types such that the firm must hire f units of each labor type to have a positive output level. While this in form resembles the single-factor model, it effectively places a distortionary quota on the demand of labor. This fixed cost has the added advantage of being denominated in units of labor, which is unaffected by pricing changes.The second type involves deducting from output as a whole. In addition to being non-distortionary, this type of fixed cost also ends up being more similar to the one-factor fixed cost in terms of mathematical characteristics. Thus, our production technology is as follows:

$$q = \phi(S^{\alpha}U^{1-\alpha}) - f \tag{2.5}$$

Here $\alpha > 0.5$ to ensure that skilled workers are more productive (all else being equal) than unskilled workers. We then have a representative firm's problem:

$$\underset{s,u}{Min} : w_s S + w_u U \tag{2.6}$$

$$\sum q_i(\phi) = \phi(S^{\alpha}U^{1-\alpha}) - f \tag{2.7}$$

Taking first order conditions for an interior solution and solving we find the conditional factor demands:

$$U = (\frac{f+q}{\phi})(\frac{1-\alpha}{\alpha}\frac{w_s}{w_u})^{\alpha} \tag{2.8}$$

$$S = (\frac{f+q}{\phi})(\frac{1-\alpha}{\alpha}\frac{w_s}{w_u})^{\alpha-1} \tag{2.9}$$

Which gives us marginal cost for a firm with productivity parameter ϕ of:

$$mc(\phi) = \frac{w_s^{\alpha}}{w_u^{\alpha-1}}\phi^{-1}(\frac{1}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}}) \tag{2.10}$$

Since we have CES preferences for consumers and monopolistic competition, we have optimal price equal to marginal cost multiplied by a markup:

$$p(\phi) = (\frac{\sigma}{\sigma-1})\frac{w_s^{\alpha}}{w_u^{\alpha-1}}\phi^{-1}(\frac{1}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}}) \tag{2.11}$$

Substituting into aggregate demand and we have optimal output of:

$$q(\phi) = (\frac{\sigma}{\sigma-1})^{-\sigma}\phi^{\sigma}(\frac{w_s^{\alpha}}{w_u^{\alpha-1}})^{-\sigma}(\frac{1}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}})^{-\sigma}P^{\sigma-1}\sum(w_iL_i) \tag{2.12}$$

which gives us the market clearing level of factor demand:

$$S = [f+\phi^{\sigma}\underbrace{(\frac{\sigma}{\sigma-1})^{-\sigma}(\frac{w_s^{\alpha}}{w_u^{\alpha-1}})^{-\sigma}(\frac{1}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}})^{-\sigma}P^{\sigma-1}\sum(w_iL_i)]}_{Z}\phi^{-1}\underbrace{(\frac{1-\alpha}{\alpha}\frac{w_s}{w_u})^{\alpha-1}}_{B_s} \tag{2.13}$$

$$U = [f+\phi^{\sigma}\underbrace{(\frac{\sigma}{\sigma-1})^{-\sigma}(\frac{w_s^{\alpha}}{w_u^{\alpha-1}})^{-\sigma}(\frac{1}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}})^{-\sigma}P^{\sigma-1}\sum(w_iL_i)]}_{Z}\phi^{-1}\underbrace{(\frac{1-\alpha}{\alpha}\frac{w_s}{w_u})^{\alpha}}_{B_u} \tag{2.14}$$

Interestingly, using this production technology results in the case where under certain conditions, the demand of both labor inputs declines as productivity increases: Taking the derivative of labor demand for skilled workers with respects to ϕ yields:

$$
\begin{aligned}
\frac{dS}{d\phi} &= \sigma\phi^{\sigma-1}Z\phi^{-1}B_s - (f + \phi^{\sigma}Z)\phi^{-2}B_s \\
&= \phi^{-2}B_s(Z\phi^{\sigma}(\sigma - 1) - f)
\end{aligned}
\tag{2.15}
$$

Thus if ϕ is sufficiently small (or conversely, if fixed costs are sufficiently high), such that $(A\phi^{\sigma}(\sigma - 1) - f) < 0$, increases in ϕ can result in decreased labor demand.

We assume that such low levels of ϕ would result in the firm exiting prior to engaging in any kind of production. Thus for all firms that do not exit, we assume labor demand is always increasing in ϕ. That is, we assume that f is low enough such that $f < A\phi^{\sigma}(\sigma - 1)$ in all equilibria.

From the above we note that if we take the ratio of the two factor demands we can eliminate much of the complexity in the equation:

$$
\frac{S}{U} = (\frac{1-\alpha}{\alpha}\frac{w_s}{w_u})^{-1} \tag{2.16}
$$

Imposing full employment results in:

$$
\begin{aligned}
\frac{S}{U} &= \frac{L_s}{L_u} = \psi \\
\psi &= (\frac{1-\alpha}{\alpha}\frac{w_s}{w_u})^{-1} \\
w_u &= \psi\frac{1-\alpha}{\alpha}w_s
\end{aligned}
\tag{2.17}
$$

Since the ratio of demands is independent of productivity ϕ, the ratio of demands for individual firms is also the ratio of demand of the industry as a whole. So by looking at aggregate demand of each type of labor, it allows us to derive the wage ratio of skilled and unskilled workers as a function of parameters. In particular, assuming technology and preferences do not shift, wages are dictated by the ratio of endowments of labor supplies. It is also important to note that the wage ratio holds regardless of the number of firms in the market. Wages will increase in equal proportion if demand for labor increases. We can derive profits for a firm with productivity ϕ as:

$$\pi(\phi) = p(\phi)q(\phi) - (f + q(\phi))\phi^{-1}[\frac{1}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}}]\frac{w_s^{\alpha}}{w_u^{\alpha-1}}. \tag{2.18}$$

Rearranging and we arrive at:

$$\pi(\phi) = \phi^{\sigma-1}A^{1-\sigma}(\frac{\sigma}{\sigma-1})^{1-\sigma}P^{\sigma-1}\sum(w_iL_i)\frac{1}{\sigma} - \frac{f}{\phi}A \tag{2.19}$$

$$where \quad A = [\frac{1}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}}]\frac{w_s^{\alpha}}{w_u^{\alpha-1}}$$

Imposing the zero profit condition and rearrange to solve for the minimum cut off productivity $\phi*$, below which a firms exit instead of engaging in production gives:

$$f = \phi *^{\sigma} A^{-\sigma}\sigma^{-\sigma}(\sigma-1)^{\sigma-1}P^{\sigma-1}\sum(w_iL_i). \tag{2.20}$$

Entrepreneurs who wants to enter the market must pay an entry cost f_e, after which is sunk. In a departure from Melitz's model, this entry cost is denominated in the composite price and is the same for all firms. Upon entering the market, the entrepreneur finds out their productivity and decides if he wants to begin production or exit the market. Firm productivity is drawn from a fixed distribution $g(\phi)$ with a cumulative distribution $G(\phi)$ with $\phi > 0$. Imposing a free entry condition where firms enter until expected profits over the distribution of productivity $G(\phi)$ equal to the cost of entry f_e:

$$fA\int_{\phi*}^{\infty}[\phi^{-1}(\frac{\phi}{\phi*})^{\sigma} - 1]dG(\phi) = f_e \tag{2.21}$$

To further examine the model and analytically solve for the welfare measures, a distribution needs to be specified. In this case, we follow Helpman

(2010)'s example in using the Pareto distribution for its memoryless property. Allowing the distribution to retain its shape regardless of truncation point:

$$g(\phi) = \frac{\alpha\phi_m^\alpha}{\phi^{\alpha+1}} \quad \forall\phi \geq \phi_m$$
$$G(\phi) = 1 - \left(\frac{\phi_m}{\phi}\right)^\alpha \quad \forall\phi \geq \phi_m$$

applying this distribution to (2.21) yields:

$$k\phi_m^k f A \int_{\phi*}^{\infty} [\frac{\phi^{\sigma-k-2}}{\phi*^\sigma} - \phi^{-k-2}]d\phi = f_e \tag{2.22}$$

We can solve this equation for the cut-off productivity for operations in autarky:

$$\phi*^A = \phi_m^{\frac{k}{k+1}}(\frac{f}{f_e})^{\frac{1}{k+1}}(\frac{\sigma}{(1+k-\sigma)(k+1)})^{\frac{1}{k}}A^{\frac{1}{k+1}} \tag{2.23}$$

Having derived the cut off productivity, we can now determine real wages using the wage ratio derived earlier. Note first that:

$$\begin{aligned} w_u &= \psi\frac{(1-\alpha)}{\alpha}w_s \\ w_sL_s + w_uL_u &= w_sL_s(1+\frac{1-\alpha}{\alpha}) \\ &= w_sL_s\frac{1}{\alpha} \end{aligned} \tag{2.24}$$

We substitute this and equation (2.23) into the zero profit condition to derive:

$$\begin{aligned} f &= \phi_m^{\frac{k\sigma}{k+1}}(\frac{f}{f_e})^{\frac{\sigma}{k+1}}w_s^{k+1-k\sigma}\psi^{\frac{(\alpha-1)(k+1-\sigma)}{k+1}}P^{\sigma-1}L_s\Lambda \\ \Lambda &= [(1-\alpha)^{\sigma-1}\alpha^{-\alpha}]^{-\sigma}(\sigma-1)^{\sigma-1}\alpha^{-1}(\frac{1-\alpha}{\alpha})^{(\sigma-1)\sigma}(\frac{\sigma}{(1+k-\sigma)(k+1)})^{\frac{\sigma}{k}}(1-\alpha)^{\frac{(\alpha-1)\sigma}{k+1}}\alpha^{\frac{-\alpha^2}{k+1}} \end{aligned} \tag{2.25}$$

Note that Λ is strictly positive if $k+1 > \sigma$.

Rearranging (2.25) and using (2.24) gives our welfare measures that are similar to the real wages utilized in Melitz's model:

$$\frac{w_s^{k-\frac{1}{\sigma-1}}}{P} = \phi_m^{\frac{k\sigma}{(k+1)(\sigma-1)}} f^{-1}(\frac{f}{f_e})^{\frac{\sigma}{(k+1)(\sigma-1)}} L_s^{\frac{1}{\sigma-1}} \Lambda^{\frac{1}{\sigma-1}} \psi^{\frac{(\alpha-1)(k+1-\sigma)}{(k+1)(\sigma-1)}} \tag{2.26}$$

$$\frac{w_u^{k-\frac{1}{\sigma-1}}}{P} = \phi_m^{\frac{k\sigma}{(k+1)(\sigma-1)}} f^{-1} \left(\frac{f}{f_e}\right)^{\frac{\sigma}{(k+1)(\sigma-1)}} L_s^{\frac{1}{\sigma-1}} \Lambda^{\frac{1}{\sigma-1}} \psi^{\frac{(\alpha-1)(k+1-\sigma)}{(k+1)(\sigma-1)}+(k-\frac{1}{\sigma-1})} [\frac{(1-\alpha)}{\alpha}]^{(k-\frac{1}{\sigma-1})} \tag{2.27}$$

Since $k - \frac{1}{\sigma-1} > 0$, the above expressions are a monotonic function of $\frac{w_i}{P}$, thus qualitative changes in its measurement are consistent with qualitative changes in real wages and welfare. Here we see that the real wage for skilled workers increases in ϕ_m and L_s while it decreases in f_e and f. Skilled wages decreases in ψ while unskilled wages unsurprisingly increases in ψ. A key difference between this model and Melitz's model then is that not only are there two separate wage rates for the two types of workers, the different supply of labor is also a departure from Melitz's model. In addition to the direct effect on wages, if a trade shock causes the supply of labor to shift, it will have different impacts on the welfare of the different worker types.

2.1.3 Trade

Now we introduce the ability to trade with other countries in this model. As in the one-factor model, we treat tariffs as a multiplier on the amount of goods needed to be shipped in order to sell one good at the foreign market. Similarly, a fixed cost must be paid to open each additional trading market for the firm. Similar to fixed costs in the domestic market, we model the fixed trade cost as denominated in the general price index and deducted from the output for trading. Thus to sell q units of goods in a foreign market, the firm must produce $\tau q + f_x$ units.

Profits:

$$\begin{aligned}\pi_d(\phi) &= \frac{r_d(\phi)}{\sigma} - [(1-\alpha)^{\alpha-1}\alpha^{-\alpha}](\frac{w_s^{\alpha}}{w_u^{\alpha-1}})\phi^{-1}f \\ \pi_x(\phi) &= \frac{r_d(\phi)}{\sigma}\tau^{1-\sigma} - [(1-\alpha)^{\alpha-1}\alpha^{-\alpha}](\frac{w_s^{\alpha}}{w_u^{\alpha-1}})\phi^{-1}f_x\end{aligned} \tag{2.28}$$

We solve for the cut off export productivity using the free entry and zero profit conditions:

$$\int_{\phi^*}^{\infty} \pi_d(\phi)dG(\phi) + N\int_{\phi_x^*}^{\infty} \pi_x(\phi)dG(\phi) = f_e, \tag{2.29}$$

where N is the number of Trading partners.

Under the zero profit condition we have the relationship:

$$\phi_x = \phi^*(\frac{f_x}{f})^{\frac{1}{\sigma}}\tau^{\frac{\sigma-1}{\sigma}} \tag{2.30}$$

We can then solve the Free-entry/Zero profit equation by once again using the Pareto distribution for productivity, yielding the open economy productivity cut off for production.

$$\phi^{*o} = \phi_m^{\frac{k}{k+1}} f_e^{-\frac{1}{k+1}} A^{\frac{1}{k+1}} [\frac{\sigma}{(\sigma-k-1)(k+1)}]^{\frac{1}{k+1}} [f + N f_x^{-\frac{k}{\sigma}} f^{\frac{k+1}{\sigma}} \tau^{\frac{(1-\sigma)(k+1)}{\sigma}}]^{\frac{1}{k+1}} \tag{2.31}$$

We can rearrange the above formula and use equation (2.24) to obtain this relationship:

$$\phi^{*o} = \phi^{*A} + \underbrace{\phi_m^{\frac{k}{k+1}} \left(\frac{N f_x^{-\frac{k}{\sigma}} f^{\frac{k+1}{\sigma}} \tau^{\frac{(1-\sigma)(k+1)}{\sigma}}}{f_e}\right)^{\frac{1}{k+1}} [\frac{\sigma}{(\sigma-k-1)(k+1)}]^{\frac{1}{k+1}}}_{\text{Positive Constant}} A^{\frac{1}{k+1}} \tag{2.32}$$

Under standard assumptions this second term is positive. Thus, as in the single factor case, we have open economy experiencing a higher productivity cut off (and thus a higher average productivity) compared to the closed economy. This is consistent with Melitz's model in that trade liberalization increases the average productivity of firms engaged in production.

Using the derived productivity cut off and inserting into zero profit conditions, we can calculate skilled worker's welfare in much the same way as autarky case:

$$\frac{w_s^{k-\frac{1}{k+1}}}{P} = \underbrace{\phi_m^{\frac{k\sigma}{(k+1)(\sigma-1)}} \left[f^{\frac{k-k\sigma+1}{\sigma}} + N f_x^{-\frac{k}{\sigma}} f^{\frac{k(2-\sigma)+(2-\sigma)}{\sigma}} \tau^{\frac{(1-\sigma)(k+1)}{\sigma}}\right]^{\frac{\sigma}{(k+1)(\sigma-1)}} f_e^{-\frac{\sigma}{(k+1)(\sigma-1)}} L_s \Lambda^{\frac{1}{\sigma-1}}}_{J} \psi^{\frac{(\alpha-1)(k+}{(k+1)(\sigma}} \tag{2.33}$$

Similar to the autarkic case, substituting the wage ratio yields:

$$\frac{w_u^{k-\frac{1}{k+1}}}{P} = J\psi^{\frac{(\alpha-1)(k+\alpha-\sigma)}{(k+1)(\sigma-1)}+(k-\frac{1}{\sigma-1})}[\frac{1-\alpha}{\alpha}]^{k-\frac{1}{\sigma-1}} \tag{2.34}$$

Real wages for both types of workers increases in ϕ_m , L_s, N while it decreases in f_x,f, τ, ψ and f_e. Furthermore, skilled real wages decreases in ψ and unskilled real wages increases in ψ.

Having established the base case for the two-factor production technology, we can now introduce additional heterogeneity within the labor force that allows for labor mobility and skill adjustments.

2.2 Worker Mobility

To account for social mobility for workers, we introduce additional changes to our two-factor model. Generally speaking there are two types of mobility for workers: geographic and aptitude. In the former case, workers may move between regions to gain access to more favourable employment conditions.

In the case of a trade model, this typically means workers leave areas that are not intensively employed by the exporting industries into regions that are intensively employed by exporting industries. We see evidence of this type of migration in both developed and developing countries, either in the form of migrant workers who shift from rural to urban centers in search of manual labor or those who move into manufacturing towns. Aptitude mobility is mostly manifested as workers who opt to obtain additional training or education to increase their marketability. This could take the form of on the job training, professional programs or earning a traditional degree.

To accomodate geographical changes, we add an additional worker type which represents workers who do not participate in production of any traded goods. These rural workers operate in a region that contains no firms but earns a fixed wage w_r and consumes goods like any other laborer. Each rural worker can forfeit a portion of their consumption E_r in order to 'move' to a region with productive enterprises and participate in the workforce - becoming an unskilled laborer. Similarly, an unskilled laborer can forfeit a portion of their consumption E_u to improve their productivity and become a skilled laborer.

Each worker draws their skill mobility cost from a fixed distribution with cumulative distribution function $F(E_u)$ for unskilled workers and $F(E_r)$ for rural workers prior to making any decisions on consumption/labor. In both cases, the costs E_u and E_r are greater than zero. These variation between individuals account for the natural differences in a worker's ability to improve their skills (or in the rural worker's case, variation on the costs of moving to a new locale). We draw the rural and urban workers from separate distributions to allow for differences in the cost of mobility between rural and urban workers.

2.2.1 Workers' Problems

Once the costs are drawn, the workers decide, before production begins, whether or not to pursue improving their productivity. They then participate in the work force as per the baseline model. Type S workers face the same problem as before because they do not move. Type R and U workers faces the following problem:

$$\underset{q(w)_{\omega\in\Omega}}{\text{Max}} : \left(\int_{\omega\in\Omega} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega\right)^{\frac{\sigma}{\sigma-1}} \tag{2.35}$$

Subject to(for unskilled workers):

$$\int_{\omega\in\Omega} q(\omega)p(\omega)d\omega \leq -\Gamma E_u + \Gamma w_s + (1-\Gamma)w_u \tag{2.36}$$

or (for rural workers):

$$\int_{\omega\in\Omega} q(\omega)p(\omega)d\omega \leq -\Gamma E_r + \Gamma w_u + (1-\Gamma)w_r \tag{2.37}$$

where Γ is an indicator such that 1 represents choosing to improve their productivity and 0 means choosing not to. Note that in the one period model, workers are paid wages and pay their mobility cost in the same period. Skill improvements also happen instantaneously, so costs are deducted from their post-improvement wages.

Thus, there exist some level of costs E_r^* and E_u^* above which productivity improvements becomes non-optimal. In the simple model with full information, these cut off costs are fixed and known and so we have in aggregate that $F(E_u^*)L_u$ unskilled workers becomes skilled and they faces a budget constraint of:

$$\int_{\omega\in\Omega} q(\omega)p(\omega)d\omega - E_u \leq w_s \tag{2.38}$$

while $(1 - F(E_u^*))\,L_u$ unskilled workers remains unskilled and retains their unmodified b.c.

A similar division exists for the rural workers and so we have five distinct types of workers: Natural Skilled workers, Trained Skilled workers, Natural Unskilled workers, Trained Unskilled workers and Rural workers.

A trained worker's optimal demand of each good becomes:

$$q(\omega) = (w_i - E_i)p(\omega)^{-\sigma}P^{(\sigma-1)} \tag{2.39}$$

and aggregate demand becomes:

$$q(\omega) = \sum_{i\in 1,2}(F(E_i^*)L_i(w_{i+1} - E_i^A) + (1 - F(E_i^*))L_i w_i) + w_3 L_3]p(\omega)^{-\omega}P^{\omega-1} \tag{2.40}$$

Where i represent worker types of u, r and s (as 1, 2 and 3 respectively). Despite the added complexity, the firm side problem remains the same and the functional form of the aggregate demand remains in the form of

$$(w_s X + w_u Y)p(\omega)^{-\sigma}P^{\sigma-1} \tag{2.41}$$

Which means we can still use the same method of simplifying through the labor demand ratio and arrive at largely the same results. Thus, the only change from the baseline model will be the composition of the labor supply ratio. The new ratio of workers post-adjustment becomes:

$$\frac{S}{U} = \frac{L_s + F(E_u^*)L_u}{L_u(1 - F(E_u^*)) + L_r F(E_r^*)} \tag{2.42}$$

Thus we can see that the shape of the distribution of the costs of upgrading skills plays a critical role in determining the welfare outcomes of the system with labor adjustments.

As seen in (2.33) and (2.34), trade liberalization increases the real wage of both skilled and unskilled workers. This pushes the maximum cost E^* threshold for choosing skill improvements for both rural and unskilled workers above autarkic levels, inducing a flow of workers as more people are able to afford skill improvements.

Under certain scenarios, such a shift in the maximum cost threshold will allow more rural workers to move into the city than urban unskilled workers to become skilled. So more workers become unskilled workers compared to skilled workers, and the wage ratio shifts against unskilled workers. One such scenario could be that a large portion of the population are rural workers who have a near-poverty level of income. While a small increase in wages would not induce a great number of people to participate in higher-level education, it would allow many to be able to afford to move to the city for better jobs. In this case we have:

$$\frac{w_s^o}{w_u^o} > \frac{w_s^A}{w_u^A} \tag{2.43}$$

Furthermore, since the rural wage rate w_r does not scale with output, as wages for urban workers increase due to trade (either skilled or unskilled) the gap between urban and rural workers increase compared to the pre-liberalization period. We should see in any empirical study that the ratio of urban mean wages to rural mean wages increase as trade liberalizes.

2.3 Demand

While the focus of this model remains squarely on the supply side of the labor-production equation, it would be imprudent to ignore the shifts in demand as a result of labor adjustments and trade liberalization.

The simple Melitz model assumes that productivity is an exogenous parameter unrelated to the functional form of the production technology. That it is a multiplier drawn at firm inception and factor utilization and efficiency remains more or less the same across different draws (thus their rate of demand for different types of labor remains more or less constant.) This is likely not to be the case, as more productive firms tend to have technological edge or are simply more capital intensive. This tend to lead to more demand for skilled workers over unskilled workers. So the production function looks more like:

$$q = \phi(S^{\alpha(\phi)}U^{1-\alpha(\phi)}) - f \tag{2.44}$$

where α is increasing in ϕ. In this form, the ratio of demand of skilled and unskilled labor is no longer constant across firms with different productivities. From a welfare perspective, this implies that if trade liberalization pushes the average productivity of firms above autarkic levels, it would shift overall demand towards more skilled workers and expanding the wage inequality. Thus, firm's labor demand changes in response to trade compounds the effect discussed above rather than diminishes it.

Similarly, this particular model assumes that firm productivity is separate from worker's productivity. This is a result of the fact that the general Melitz model imposes a fixed ϕ after a firm's inception. Realistically, the average productivity of a firm's work force is deterministic to its overall productivity. If we relax this assumption and incorporate labor productivity into ϕ, then another demand side outcome emerges: As competition increases from liberalizing markets, firms will naturally increase demand for skilled workers to increase their overall productivity in order to remain competitive. Again, this leads to increased wages for skilled workers and depressed wages for unskilled workers, further increasing the wage gap.

2.4 Summary

This model takes the general Melitz model of trade and adjusted it to accommodate labor skill heterogeneity as well as worker mobility between the skill categories. It added richness to the baseline Metliz model by allowing a more in-depth look at the changes in relative welfare between different types of workers in response to trade. The primary result of this analysis is that under normal assumptions, increased trade will result in dramatically increased wage disparities between skilled and unskilled workers. We arrive at this conclusion even when we assume there are no other market frictions that could cause changes in wage inequality.

We find that this outcome is driven primarily by labor supply changes in the wake of trade liberalization. This shift comes from two important features: First, wages of all export-utilized labor increased as a result of increased trade. Second, the costs of skill and geographic mobility is significant. The former creates incentives for workers to move in the post-liberalization period and the latter creates a separating equilibrium where workers are divided based on their individual skill mobility costs.

In the empirical work that follows, we want to determine if our observations are consistent with the outcomes predicted by the model.

3 Data and Methodology

3.1 Background

My empirical analysis focuses on variations in worker wages due to regional differences in education access costs throughout the WTO transition period in China. We focus on education access cost over the geographic mobility costs for a variety of reasons. Primarily, education costs are easier to quantify and easier to find economic proxies for that have been consistently measured. For example, very few surveys place much emphasis on distinguishing between migrant and non migrant workers, making it difficult to isolate the wage effects on just the migrants. Furthermore, of those studies that focus on migrants, little attention is paid to non-economic costs of migration. At most, one is asked the location of their 'home' region and costs of transportation. However, the bulk of the costs of economic migration (especially the type that is pervasive in China) are social rather than economic: lack of access to essential services, lack of social support structure and living away from their families. These costs are material when workers make the decision to migrate to another region and should not be discounted and yet it is nearly impossible to account for their costs on a large scale.

To effectively study the impact of education cost variation on distributional outcomes of trade liberalization we make some important assumptions. The largest of which is that the bulk of the increase in economic activity from 1995 onward is assumed to be attributed to the increased trading activity as a result of tariff liberalization. Taking as evidence that the period leading up to 1995 marked the height (and perhaps the tapering off of) of the market economy transition in China by contrasting the drastic decline of the gross industrial output of state enterprises until the mid 1990s [1]. One can see from the National Bureau of Statistics of China (henceforth NBSC) data that in 1978 state owned enterprises accounted for nearly 80% of all industrial output while in 1995 it accounted for scarcely 30%. This two decade long drop flattened out after the economic crisis in 1997 and remained steady afterwards. This suggests that the privatization of China's economy may have reached an equilibrium.

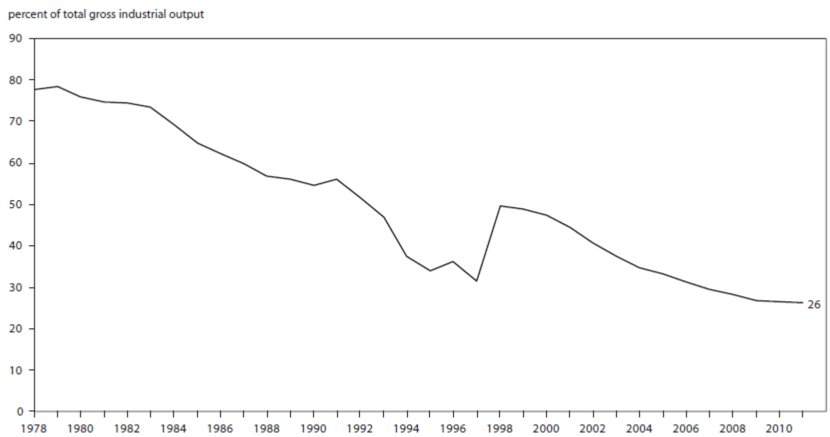


FIGURE 3.1: State Ownership of Industrial Output

2

At the same time, China's trade volume began its explosive ascent during the 1995-1997 period. Exports as a percent of GDP more than doubled, growing from 18% in 1995 to 37% in 2007. Although other factors may have been instrumental in the course of China's economic growth, none had as large of an impact as market privatization and trade liberalization. Thus I hypothesize that changes in the Chinese economy during this time can largely be

[1]Annual Data on Industries, National Bureau of Statistics of China, http://www.stats.gov.cn/

[2]Nicholas R. Lardy, "Rise of the Private Sector", Markets Over Mao, Peterson Institute for International Economics, 2014

attributed to the increase in trade and the decline in tariffs to the rest of the world.

3.2 Microdata

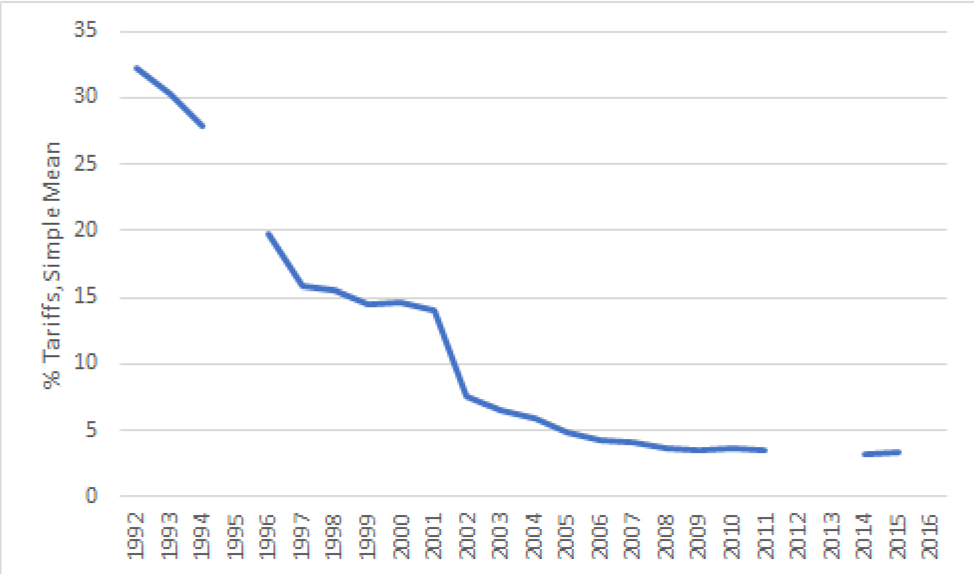
The Microdata used for the analysis of individual income is collected by the Chinese Household Income Project[3], a series of household surveys for both rural and urban Chinese households conducted by the China Institute for Income Distribution and the University of Michigan's ICPSR. This included income and personal information of some 50,000 individuals across 429 counties in 13 provinces and covers the years 1988, 1995, 2002 and 2007 . It contains detailed information on the working environment, education background, household and economic conditions of the subject. More importantly, the location of each subject is recorded to the county or township level and allows a significantly higher level of granularity in the analysis. In particular, it allows us to account for regional differences in costs in addition to changes in local economies.

There are several issues to use this data for our purposes. Primarily, because it is impossible to identify households across different sampling periods, one cannot track the changes in income in relation to the changes in tariffs. Consequently, for the purpose of this analysis, each individual at each period is treated as separate entities in distinct locations. We also look at the change in the impact of several variables on wages rather than looking at the impact of the variables on the changes on wages. Secondly, since the collection of household information is not supported by the national statistics bureau, the size of the sample is quite small compared to the population of their respective communities and even smaller compared to China's overall

[3]Chinese Household Income Project, Chinese Institute for Income Distribution, http://www.ciidbnu.org/chip/index.asp, 1988-2013

population. The sample amounts to less than 0.005% of the population, collection and sampling bias will heavily impair our ability to make inference based on this data. Finally, there have been several changes in the collection methods and collection agencies for the survey itself since inception, comparability of the data set may be compromised. To mitigate this effect, we opt to not use the post-2007 data where the objective of the survey shifted.

FIGURE 3.2: Tariffs over time, simple mean



Source: WTO Tariff Data, "http://data.worldbank.org/indicator/TM.TAX.MRCH.WM.AR.ZS", accessed July 25, 2017

We choose three time periods as the focus of our investigation: 1995, 2002 and 2007. While the WTO accession was officially ratified in 2001, China began to curtail tariffs some time prior in preparation. One could trace the steady decline of tariffs to around 1995 and that acts as a good starting point for our 'before' snapshot. 1988 is another possible candidate but the data available in this earlier survey was less complete and the level of documentation also fails to clearly identify the households in a usable manner. Additionally, the period between 1988-1995 encompasses an era of growth more related to the market economy transition rather than trade liberalization.

The year 2002 is another good period for study not only because of data availability but because it represent the time period immediately after most accession demands were being met, thus we see the result of the transitioning between relatively high tariffs and relatively lower tariffs. This is important to establish the dynamics of economic outcomes during trade liberalization rather than simply capturing the static beginning and ending phases of the economy. It gives us greater insight to the direction of movement as well as the speed at which variables transitioned during the liberalization process.

Finally, 2007 is towards the end of the transition period, once nearly all tariffs have been lowered to stipulated levels. We take this as the post-transition level of the economy.

3.3 Location Specific Data

To determine the local level of education access, I used China Data Online's data on secondary school enrollment at the county and city level[4]. For those counties that were missing from the dataset, I collected the information from China's ministry of education's annual snapshots and the individual county's annual reports[5].

As per Vailancourt(1985) education costs can be broken down to several sub-categories: Public costs include government transfers, subsidies and other funding. Private cost, which is more pertinent to our analysis, includes tuition, books, extra cost of living expenses and opportunity cost of lost wages. We make a slight departure from the theory by pinning the mobility costs not to individual workers but rather to their region. Even though

[4]County Level education database, China Data Online, http://chinadataonline.org/, accessed July 10, 2017

[5]Ministry of Education Annual Snap Shot, Ministry of Education, http://en.moe.gov.cn/, accessed July 5, 2017

the surveys included some personal information regarding education attainment and participation, there was not enough detail in the questions nor was there sufficient consistency across the different years to establish a cost by individual basis. This will have some ramifications in our results as region wide mobility costs have slightly different impact than invidual variations, particularly in the restrictive labor market in China.

Enrollment in public secondary schools is chosen as a proxy for location specific cost of education for several reasons. Firstly, since China's education system is publicly funded until grade 12, there are no significant cost variations among the counties. This simplifies the enrollment decision to willingness to participate without selecting for those who are able to afford the costs. Since secondary education is mandated by the government, it also minimizes selection for ability. More importantly, secondary education enrollment is chosen because it brackets the period where one is old enough to have an reasonable alternative to school, thus percentage participation in the school system reflects perceived economic incentives for continuing education. Finally, there is significant empirical evidence that education outcomes as a proxy for skill disparity has a significant impact on later-life wage distribution(see Berdard and Ferrall (2003)).

While in most western countries the enrollment in public school systems would be strongly skewed by regional demographic variation, this effect is less pronounced in the case of China. Due to the restrictive nature of the Hukou system, the shifts in demographics due to employment and other temporary migrations as a result of economic changes is largely mitigated. Since the registered home region of an individual or household is largely fixed unless given very specific instances, the system dampens the recorded demographic changes in a number of ways. Primarily, those who migrate to other regions without changing hukou do not receive many of the social services available to residents. One of these services is access to the public education system. This means that children of migrant workers do not enroll in the system or more likely, they are simply left in their home counties and registered with the local school board. On the other hand, since migrant workers without a hukou do not count as a resident of their working county, the population figures tend not to reflect the size of the migrant worker community.

In fact, many government statistics list separate figures for registered residents and the average population that lives within the county. In effect, this means that the recorded demographics of China is much more static than almost anywhere in the world - households tend to be registered in their birth regions regardless of their physical location. This allows for a reasonably accurate estimation of the cost of education enrollment by holding the ratio of children to adults relatively constant across all regions.

also included as part of the analysis the GDP per capita information for each of the counties, collected from CDO[6] and from the National Bureau of Statistics of China's annual snapshots[7]. Since regional variations in economic growth tend to have much more variance than most western countries, it is important to account for the local growth's impact on wage growth. Furthermore, GDP growth is a good proxy for the region's exposure to trade in general, with southern and coastal regions having the largest increase in GDP per capita as well as the highest exposure to trade. The GDP data is deflated using CPI of both urban and rural regions at each period.

More relevantly, GDP has two distinct effects on the ease of access to education. On one hand, increased (real) GDP per capita implies greater average income and thus larger household budgets. We can then infer that education costs would then be a smaller portion of the annual consumption of any

[6]County Level Economic database, China Data Online, http://chinadataonline.org/, accessed July 10, 2017

[7]NBSC Annual statistics summary, National Bureau of Statistics, http://www.stats.gov.cn, accessed June 5, 2017.

individual worker. This decreases the relative opportunity costs of purchasing education over other consumer goods and thus decrease the real cost of education. Conversely, increased real GDP per capita without increasing in the wage gap between education cohorts would imply an *increase* in education costs as the gains from improved skills shrinks as a proportion of current wages. Thus it is important to ensure that the population experiences an increasing education wage gap so that regional GDP is positively correlated with education access.

However, since GDP calculations are notoriously unreliable for most Chinese data sources, where rampant inflation of GDP figures are common, instead of using the levels of GDP per capita for my analysis, I ranked the selected counties and use the ranking as the basis of my analysis. With the rationale being that in spite of the persistent and systematic doctoring of GDP figures, the relative GDP comparison will have somewhat higher accuracy. Since we are only interested in the relative exposure to trade rather than absolute, it is not necessary to pin down an accurate level of GDP per capita.

TABLE 3.1: Regional Data Summary Statistics

Variable	**Mean**	**Std. Dev.**	**N**
Urban			
Enrollment Ratio	4.155	1.659	215
GDP per capita	7.717	7.372	215
Rural			
Enrollment Ratio	4.349	1.404	214
GDP per capita (10,000)	3.817	3.413	214

3.4 Empirical Method

To provide support for the theoretical model, several relationships should be investigated prior to more careful empirical analysis. Firstly, one important criteria for the model is that education returns are positive and increases as tariffs fall or that w_s and thus w_u increases as trade increases. In the traditional model of trade, factors employed intensively or factors that are utilized specifically in the exporting industry will realize wage gains in response to trade liberalization. Thus, for developing countries experiencing a manufacturing boom, one would expect the low skill workers that make up much of the manufacturing workforce to have the greatest gains. On the other hand, skilled workers used less intensely in exporting industries would experience less wage growth. Combined, the traditional model predicts that developing countries should have a narrowing wage gap between skilled and unskilled workers during trade liberalization. In contrast, Melitz model predicts that all workers experience wage gains during trade liberalization and in the two-factor variant, the wage gap would likely increase or remain constant. Since an increasing wage gap is an important driver in incentivizing the flow of workers, we calculate the wage gap between college and high-school educated individuals for each of our three time periods.

Secondly, one assumption made in the model was that rural areas are less influenced by changes in trade and rural wages are depressed relative to urban wages. This provides incentive for rural workers to move to urban areas and thus allows geographic mobility cost to play a role in determining wage outcomes. It is important then, to look at the changes in wage ratio of workers in urban and rural areas and determine if this wage gap is increasing or decreasing.

TABLE 3.2: Education Wage Gap

	1995	2002	2007
Male			
College	7942.11	14806.39	40389.04
High School	6686.75	10494.97	32078.42
Wage Ratio	1.19	1.41	1.26
Female			
College	7753.30	14060.00	34005.42
High School	6497.94	9748.58	25694.80
Wage Ratio	1.19	1.44	1.32

Table 3.2 is the result from analyzing our data using similar methodologies as Caponi and Plesca (2009). We note that education returns has consistently increased during the liberalization period for both male and females. Supporting our case for linking tariff decreases with increased demand for skilled workers. It is also somewhat important to show the change of the wage disparity between the top and bottom earners for both Urban and Rural regions. As predicted by the model, large declines in τ results in increasing wage gap between both the top and bottom 10% of earners in each region and also increases the wage gap between the regions.

One important aspect of this disparity in wage income that is not discussed in the theoretical framework is the fact that as demand for skilled workers become more prevalent, education becomes a strong signalling tool for high ability (See Berdard (2001)) and thus there is an increased demand for higher levels of education. This stronger signal at a higher level increases the wage disparity between college and non-college educated workers. Furthermore, as less talented individuals remain in the lower education brackets, the incentive to finish lower level degrees declines and one sees more drop outs earlier. This further degrades the income levels of low-ability workers. Nevertheless, this outcome is part of and amplifies the outcomes associated with mobility cost reductions rather than diminishes it.

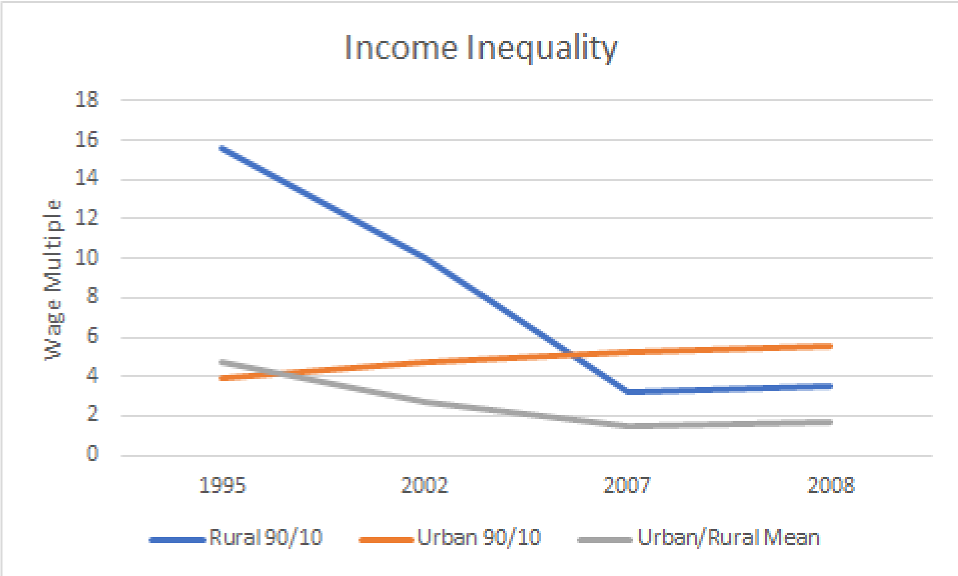


FIGURE 3.3: 90-10 wage gap for Urban and Rural workers. Calculated using CHIP data set for individuals age 16+ and fully employed in the year of survey.

Figure 3.3 is the result of our analysis on the wage gap between the top and bottom 10% of workers in both rural and urban areas. Additionally, comparisons were also made between urban and rural worker's mean wages. Consistent with other studies on the wage inequality in China, we notice a distinct trend for the richer portion of the population to capture a higher portion of the gains from trade (from the higher rate of growth of wages of the upper half of the income bracket). Furthermore, we note that despite the declining wage gap between the poorest and the richest in the rural communities, the opposite is true for those who live in urban areas. Furthermore, the wage gap between the urban and rural closes during the adjustment period while we see a small uptick in the post-adjustment period in 2008.

The changes in the rural communities can be attributed to two distinct effects: One is the direct result of migrant workers leaving rural communities to earn higher income in the urban areas, this drives up overall income and increases the earning of those who can afford to migrate. Secondly, once the workers migrate out of their rural communities, the supply of labor in those areas shrinks and drives up the wages for those who are poorer. Other factors, such as government's policy to transfer payments to those who remain in rural areas as a social security measure also greatly increased the income of those who remain in the rural regions. This accounts for another portion of the shrinking wage gap. In this particular case, one can attribute the sharp down-tick of rural poor wage growth in the post-adjustment period to the sudden and significant increase in consumer prices in rural areas in the 2007-2008 period, likely as a result of the global recession.

The changes in the urban communities is largely as predicted by the model: Increases in demand of skilled labor greatly increased the earning potential of those who are at the top half of the earning potential. On the other hand, steady increase in supply of low skilled workers who migrated from rural areas increased competition for the unskilled urban residents - contributing to the increase in the wage gap. What is more interesting perhaps is the decline in the wage difference between the median urban and rural workers. My model does not have enough granularity in differentiating the ability of workers to provide an explicit explanation for the decline in the difference in the median wages, instead it predicts the opposite effect for the overall shift in wages. That is, there should be an increase in the urban-rural wage gap during this period. However, a key difference between the model's prediction and this data set is the way it categorizes workers. Since workers are grouped by their 'home' regions, those workers who moved to the city to earn income would still be considered 'rural' workers in the sample. Under these circumstances, one can see that the average wages must be increasing in both areas compared to pre-adjustment. More importantly, since I assumed that the labor ratio skews in favour of high skilled workers, the average wage must be increasing slower in urban areas compared to rural areas. Thus, it indirectly explains the shrinking difference in rural-urban wage gap.

TABLE 3.3: Average GDP by region

	Rural Mean	Urban Mean
1995	3.512	4.607
2002	3.398	7.716
2007	4.369	7.813

Another possible reason for this decline is that rural areas have simply urbanized in the intervening years and that production has steadily moved into previously rural communities. Comparing the difference in GDP per capita of the list of communities in the Rural and Urban regions in table 3.3, I note that while GDP grew in both areas in all affected years, the changes in GDP do not follow a similar trend to the changes in wage gap so it is unlikely that the shifting of goal posts in labeling the communities is a major contributor to the changes in earning of residents.

To estimate the relative importance of education costs on wage returns in this period, I adopt similar methodologies from Hakobyan and Maclaren(2010) by constructing an estimation equation from a worker's individual traits and the location specific traits that effect education costs.

The Education Access Index is constructed by multiplying the ranking of both enrollment and GDP then normalizing against the maximum. This gives the relative ease of enrollment compared to the other regions in the sample.

$$Index_i = \frac{rankEnroll_i \times rankGDP_i}{max(rankEnroll \times rankGDP)} \tag{3.1}$$

Then, following standard approaches to estimating wage in labor literature, this gives us the initial estimating equation of:

$$Log(Wage_{ij}) = \beta_1 Age_j + \beta_2 Age_j^2 + \beta_3 Education_j + \beta_4 Sex_j + \beta_5 Index_i + \epsilon_j \tag{3.2}$$

Where j indexes each observed workers, i indexes the regions the worker belongs to and we use the usual Mincer variables plus the location specific education access rank.

4 Results

4.1 Baseline Results

Table 4.1 shows the main regression results from equation (3.2). First, we note that while education access was relatively unimportant for urban areas at the beginning of the transition period, once tariffs were lowered, it became much more significant both economically and statistically as an indicator for higher average wages. Towards the end of the liberalization period, the top and bottom urbans regions with respects to relative cost of education had a wage difference of over 20%.

Additionally, we find that rural sectors have the opposite outcomes on the enrollment parameter, exhibits declines in the correlation throughout all the periods examined. One possible explanation for this decline is the increased disparity between perceived benefits of education and actual opportunity cost of not working. Assuming that rural sectors are less exposed to foreign markets and that rural workers set their expectations based on national or urban averages. Then those who live in regions with lower access cost to education may incorrectly overvalue the effects of obtaining higher productivity, leading to an oversupply of skilled workers, driving down average wages.

For the most part, the estimates for the personal characteristics remain consistent with similar works. Women, workers of lower education and workers nearing retirement tend to have a lower than average wage income.

TABLE 4.1: OLS Estimates on Log Wages

	(1) 1995 Rural	(2) 1995 Urban	(3) 2002 Rural	(4) 2002 Urban	(5) 2007 Rural	(6) 2007 Urban
Index	1.525***	-0.00608	0.859***	0.151***	0.114***	0.210***
	(0.144)	(0.0286)	(0.0620)	(0.0329)	(0.0271)	(0.0328)
HS	0.513**	0.344***	0.217***	0.264***	0.0227	0.190***
	(0.173)	(0.0187)	(0.0411)	(0.0159)	(0.0266)	(0.0208)
College	0.951	0.485***	0.521***	0.562***	0.0678***	0.594***
	(1.060)	(0.0158)	(0.0521)	(0.0166)	(0.0188)	(0.0210)
Age	0.0231	0.181***	0.0494***	0.0440***	0.0434***	0.0558***
	(0.0170)	(0.00222)	(0.00645)	(0.00448)	(0.00312)	(0.00544)
Age^2	-0.000449*	-0.00180***	-0.000644***	-0.000348***	-0.000681***	-0.000696***
	(0.000209)	(0.0000256)	(0.0000829)	(0.0000553)	(0.0000415)	(0.0000677)
Female	0.0707	-0.187***	-0.00851	-0.178***	-0.247***	-0.302***
	(0.0975)	(0.0138)	(0.0321)	(0.0127)	(0.0139)	(0.0157)
Constant	5.740***	4.081***	6.930***	7.799***	8.920***	8.603***
	(0.336)	(0.0475)	(0.118)	(0.0901)	(0.0581)	(0.108)
Observations	1752	12470	6013	8812	8763	6783
R^2	0.073	0.439	0.061	0.171	0.081	0.183

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The one instance where estimates deviate from norm is the education parameters for 1995 rural, with negative and statistically insignificant estimates. This suggests that education simply did not correlate with income prior to the economic boom in rural China. Finally, it is important to note that the mincer type equation appears to have relatively higher explanatory power in urban areas compared to rural regions. With R^2 of rural regions consistently at below 0.1 while urban regions have comparable R^2 to what one would expect from similar wage decompositions.

These results provide some support for the proposed theory as the sign and direction of change for urban sectors match the expectations derived from the model. Conversely, the mismatch between rural results and model predictions suggests that social mobility through education may be a smaller factor in those regions and that as suggested by the model, geographical mobility may play a much bigger role.

4.2 Selection and Robustness

One important issue in the above estimation is that the ability and personal characteristics of the worker could influence his propensity to work. Since those who are unemployed report wages of 0, any estimate that do not correct for selection into employment will over estimate the impact of those variables highly correlated with innate ability. Furthermore, since we expect that each worker will accept work only if the offered wage is higher than his reservation wage, the sampled wages will be biased upwards.

Thus we append to our main equation an additional step to correct for the selection effect of working to produce the following two-step estimation. Following Heckman(1979), the first stage estimation is a probit regression that estimates the propensity for observing a positive wage outcome given a set of personal characteristics. When we correct for the propensity for employment with the usual characteristics of Sex, Marriage, Education, Age and Race, we have:

$$P(Employment_j = 1|X) = \Phi(\gamma_1 Minority_j + \gamma_2 Sex_j + \gamma_3 Education_j + \gamma_4 Age_j + \gamma_5 Married_j + \epsilon_{1j}) \tag{4.1}$$

The second stage incorporates the first stage estimates to correct for selection into working:

$$lnWage_{ij} = \beta_1 Age_j + \beta_2 Age_j^2 + \beta_3 Education_j + \beta_4 Sex_j + \beta_5 Index_i + \lambda_j (X_j \gamma) + \epsilon_{2j} \tag{4.2}$$

Here the inverse Mills ratio evaluated at γ is λ and is entered as a regressor in the original OLS estimation, effectively treating the selection bias problem as one of omitted variable bias. To further complicate matters, since our selection criterion for employment relies on the survey's reporting of employment status of the last month, we run into the issue of individuals who are working part time or who are working only for part of the year. Due to the wildly fluctuating level of total income over the entire year, it is not clear if it is possible to tease out the overall employment status from just wages alone. Thus we calculate hourly wages as an alternative to total annual income so there is no need to arbitrarily select a cutoff based on annual wages.

To calculate hourly wages, we use the self-reported average days worked per week and days unemployed statistics in the surveys to approximate the total hours worked in the past year:

$$HourlyWages = \frac{TotalAnnualWages}{52 \times [(DaysWorked) - Unemployeddays)] \times HoursWorked} \tag{4.3}$$

Any wages below 50% of the minimum wage (est. in 1994, 2001 and 2008)[8] are dropped as we assume that these low reported wage to be indistinguishable from unemployment. Any workers below the age of 16 are also not considered in our analysis.

TABLE 4.2: Partial results for Heckman Two-Step Estimation on Log Wages

	(1) 1995 Rural	(2) 1995 Urban	(3) 2002 Rural	(4) 2002 Urban	(5) 2007 Rural	(6) 2007 Urban
lnwage						
Index	1.147***	-0.0240	0.714***	0.189***	0.103***	0.198***
	(0.0906)	(0.0245)	(0.0554)	(0.0436)	(0.0250)	(0.0323)
select						
athrho						
Constant	-1.681***	-0.187***	-1.992***	-0.107***	-1.282***	-0.340***
	(0.0481)	(0.0496)	(0.0513)	(0.0297)	(0.0248)	(0.0514)
lnsigma						
Constant	0.880***	-0.546***	0.835***	-0.249***	-0.243***	-0.440***
	(0.0216)	(0.00780)	(0.0127)	(0.00760)	(0.0107)	(0.0105)
Observations	21526	12824	24953	15779	19665	11181

Standard errors in parentheses. For full results see Appendix A.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From our results in Table 4.2, we find that even after correcting for selection we still retain a largely positive and statistically significant relationship between relative education access and the income of workers in the region.. Since the value of the Heckman estimation does not differ significantly from the OLS estimates, nor does it show an obvious trend of deflation/inflation, we can infer that the exclusion of part time and unemployed workers did not significantly impact the accuracy of the estimation.

One other concern regarding the original estimation is that there is the possibility that the results are driven by the way our underlying index was

[8]"Regional minimum wage levels", Ministry of Human Resources and Social Security, http://www.mohrss.gov.cn, accessed July 3, 2017

constructed. More importantly, since each component of the index represents a different aspect of the cost of education, it is useful to determine the strength and direction of the impact of thesse variables independently. To that end, I decomposed the Index and performed a similar estimation using the two base variables of enrollment Ratio and GDP without ranking or normalization. The new estimation equation is:

$$lnWage_{ij} = \beta_1 Age_j + \beta_2 Age_j^2 + \beta_3 Education_j + \beta_4 Sex_j + \beta_5 GDP_i + \beta_6 Enrollment_i + \epsilon_j \quad (4.4)$$

TABLE 4.3: Partial Results for Decomposed OLS estimates on Wages

	(1) 1995 Rural	(2) 1995 Urban	(3) 2002 Rural	(4) 2002 Urban	(5) 2007 Rural	(6) 2007 Urban
Enrollment	28.24**	18.02	15.72	121.7	-86.33	-874.1***
	(9.896)	(21.35)	(11.18)	(64.03)	(126.8)	(162.6)
GDP	57.41***	217.2***	199.8***	650.7***	536.2***	434.2***
	(5.138)	(12.55)	(5.287)	(21.94)	(45.81)	(36.94)
Constant	-13.27	-2284.8***	-91.31	-4021.9**	9181.4***	-1026.3
	(125.7)	(517.3)	(88.69)	(1277.0)	(1828.9)	(4571.6)
N	14649	9470	30227	8836	8784	6783
R^2	0.015	0.132	0.133	0.212	0.037	0.095

Standard errors in parentheses. For full results see Appendix A.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.3 shows that while the coefficient on the GDP variable remained (unsurprisingly) consistently positive and statistically significant throughout all periods and regions, the enrollment coefficient is only positive for four of the six tested datasets and largely not statistically significant. This implies that some component of the results are not robust to ranking the variables or are driven by the overall economic activity overshadowing any gains from non-cost related improvements to education access. However, it is inherently difficult to separate the growth in economic activity and the decline of education costs as an important part of costs is the relative cost of tuition and the opportunity cost of lost wages. What we can conclude from this decomposition is that in these particular samples, the effect of increased opportunity cost of lost wages is eclipsed by the decline in the relative expense of tuition as overall income rose.

Similarly, we reconstructed the selection corrected estimation with the decomposed variables as well. Table 4.4 shows that as with the case of the uncorrected OLS estimates, we can attribute much of the change in wages to the GDP component of the index and that the enrollment ratio itself is not a significant indicator for wage growth.

TABLE 4.4: Partial results for decomposed Heckman Two-Step Estimation on Log Wages

	(1) 1995 Rural	(2) 1995 Urban	(3) 2002 Rural	(4) 2002 Urban	(5) 2007 Rural	(6) 2007 Urban
lnwage						
Enrollment	-0.0679***	-0.0105**	-0.0341***	0.00557	0.00151	-0.0260***
	(0.0147)	(0.00322)	(0.00847)	(0.00607)	(0.00428)	(0.00378)
GDP	0.0850***	0.0341***	0.0974***	0.0441***	0.0229***	0.0155***
	(0.00460)	(0.00188)	(0.00407)	(0.00207)	(0.00148)	(0.000866)
Constant	1.553***	-1.070***	3.698***	0.359**	1.540***	1.074***
	(0.215)	(0.0969)	(0.129)	(0.137)	(0.0605)	(0.105)
select						
athrho						
Constant	-1.530***	-0.251***	-1.890***	-0.140***	-1.294***	-0.318***
	(0.0504)	(0.0519)	(0.0605)	(0.0284)	(0.0249)	(0.0502)
Observations	21526	12824	24953	15779	19665	11181

Standard errors in parentheses. For full results see Appendix A.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As a final exercise, and to ensure that the trend and sign of our estimation is not a property of the variable we have selected to approximate education costs, I repeated the OLS estimation with attendance rate of national university qualification exam. The attendance rate of the specific region is calculated as the percentage of individuals who attempted the exam over the number of people who participated in the survey in the same region. This gives us an idea of the portion of people who wanted to attend tertiary education on a region by region basis.

The main problem with using the exam attendance ratio as a proxy for ease of access to education is that there is a significant ability barrier to entry for tertiary education compared to secondary education thus it has a strong inherent bias towards those with higher natural ability compared to secondary enrollment ratio. Furthermore, the survey itself did not attempt to collect data on the national survey participation until 2002, thus we have a somewhat incomplete view of the series using this variable. Nevertheless, we can evaluate our main result by looking at the sign and significance of the estimated parameter coefficients in this regression. Replacing the education index in equation (3.2) with the exam attendance variable gives us the new estimation equation and results:

$$lnWage_{ij} = \beta_1 Age_j + \beta_2 Age_j^2 + \beta_3 Education_j + \beta_4 Sex_j + \beta_5 ExamRate_i + \epsilon_j \tag{4.5}$$

We can see from table 4.5 that even using a weaker indicator for education access cost, there is still strong evidence that it is a major factor in the wage income of residents. In all three cases, the coefficient is economically and statistically significant. Since Exam Rate is a ratio between 0 and 1, we interpret the coefficient estimates as the difference between a region with no one willing to participate in the national exams and one who had 100% participation rate is an increase in wages of 267% in 2002 in Urban areas. In other words, a 1% increase in the exam participation rate translates to2.6% increase in average wages. Since the top and bottom 10 percentile of participation rates differ by around 15%, this accounts for nearly 39% in the average wage differential between the two regions.

TABLE 4.5: OLS Estimates on Log Wages

	(1) 2002 Urban	(2) 2007 Rural	(3) 2007 Urban
ExamRate	2.670***	3.581***	0.779***
	(0.145)	(0.302)	(0.132)
HS	0.247***	0.0355	0.185***
	(0.0149)	(0.0251)	(0.0213)
College	0.539***	0.0773***	0.575***
	(0.0156)	(0.0179)	(0.0217)
Age	0.0468***	0.0431***	0.0537***
	(0.00424)	(0.00297)	(0.00559)
Age2	-0.000397***	-0.000689***	-0.000671***
	(0.0000524)	(0.0000395)	(0.0000696)
Female	-0.183***	-0.255***	-0.306***
	(0.0119)	(0.0131)	(0.0161)
Constant	7.555***	8.874***	8.612***
	(0.0857)	(0.0552)	(0.113)
Observations	9667	9765	6885
R^2	0.201	0.096	0.171

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Conclusion

In this paper I attempted to explain the distributional outcomes of trade liberalization in China's post WTO accession period by introducing labor mobility into Metliz's classic trade model with firm heterogeneity. By focusing on the shifting of types of labor across rural and urban areas, it can be demonstrated that the variation of the cost of social mobility can play a large role in the distribution of the gains from trade.

Specifically, we have the somewhat contrarian result that urban unskilled workers, despite being relatively more wealthy and have better access to market than the rural poor, fare the worst as a result of multilateral trade liberalization. This stem largely from the assumption that disparity in the cost in geographical mobility and skill mobility is significant and thus it is cheaper for the more numerous rural workers to move into the cities than it is for the unskilled urban natives to obtain education.

I find some support for the theoretical model in the empirical work done on data from the Chinese Household Income Project. Preliminary analysis provided support for the theory as I found an increased 90-10 wage gap growth in the urban sectors while the opposite effect in rural regions. Similarly, we find little to no growth in the education wage gap in the rural regions while the education premiums increased in Urban sectors. Suggesting that education plays a much more significant role in areas more effected by trade.

Initial results on education access suggested that there is a positive and increasing trend in the relationship between education access and wage income in the urban regions. Further, we found that there is strong evidence that the outcome is driven largely by the opportunity cost reduction of education access as a result of increased general welfare rather than ease of enrollment. However, we cannot establish the same relationship in rural sectors with any level of confidence. We conclude that while labor mobility as a result of education is a significant factor in driving wage growth in developed areas but geographic mobility remain the primary driver for wage growth in the country side.

6 Appendix

6.1 Summary Statistics on Data sets

TABLE 6.1: Summary Statistics for1995 Rural

Variable	Mean	Std. Dev.	N
Sex	1.497	0.5	21526
Age	38.398	15.453	21526
Years of Education	5.657	3.386	21526
Married	1.376	0.748	21526
Minority	1.87	0.398	21526
Total Children	0.566	0.903	21643
IncomeTotal	600.653	2948.536	21526

TABLE 6.2: Summary Statistics for1995 Urban

Variable	Mean	Std. Dev.	N
Sex	1.506	0.5	16699
Age	35.814	18.42	16694
Years of Education	9.593	3.634	15413
Married	1.446	0.744	16699
Minority	1.95	0.219	16699
Total Children	0.439	0.641	16699
IncomeTotal	5389.405	4017.64	12581

TABLE 6.3: Summary Statistics for 2002 Rural

Variable	Mean	Std. Dev.	N
Sex	1.48	0.5	34536
Age	32.916	18.577	34536
Years of Education	6.581	3.072	31970
Marital status	1.59	0.906	33829
Minority	1.853	0.354	34489
TotalChildren	1.163	0.968	34639
IncomeTotal	1017.947	2796.138	34536

TABLE 6.4: Summary Statistics for 2002 Urban

Variable	Mean	Std. Dev.	N
Gender	1.506	0.5	18744
Age	38.468	18.137	18744
Years of education	9.619	4.197	18636
Marriage	1.733	0.758	18636
Nation	1.045	0.209	18636
TotalChildren	0.366	0.547	18972
IncomeTotal	10847.641	8486.963	13919

TABLE 6.5: Summary Statistics for 2007 Rural

Variable	Mean	Std. Dev.	N
Sex	1.482	0.5	28288
Age	34.989	19.04	28274
Years of Education	7.637	2.592	19899
Married	2.893	2.381	28288
Minority	1.076	0.673	28287
TotalChildren	0.716	0.885	28430
IncomeTotal	15794.678	18053.006	9203

TABLE 6.6: Summary statistics for 2007 Urban

Variable	Mean	Std. Dev.	N
Sex	1.504	0.5	14443
Age	39.107	19.243	14442
Years of Education	11.287	3.625	11203
Married	1.871	0.779	14376
Minority	1.038	0.403	14441
TotalChildren	0.986	0.864	14443
IncomeTotal	26086.491	27205.426	7053

6.2 Regression Results

TABLE 6.7: Heckman Two-Step Estimation on Log Wages

	(1) 1995 Rural	(2) 1995 Urban	(3) 2002 Rural	(4) 2002 Urban	(5) 2007 Rural	(6) 2007 Urban
lnwage						
Female	1.492***	-0.126***	1.529***	-0.131***	-0.0321*	-0.243***
	(0.0749)	(0.0125)	(0.0502)	(0.0176)	(0.0158)	(0.0180)
HS	0.271**	0.169***	0.0785	0.196***	-0.0555*	0.169***
	(0.0833)	(0.0163)	(0.0406)	(0.0211)	(0.0238)	(0.0206)
College	0.615**	0.308***	0.339***	0.405***	-0.0599**	0.566***
	(0.228)	(0.0144)	(0.0552)	(0.0229)	(0.0183)	(0.0212)
Age	0.0233*	0.0761***	0.00373	0.0295***	0.0401***	0.0461***
	(0.0107)	(0.00481)	(0.00621)	(0.00680)	(0.00295)	(0.00546)
Age2	-0.000139	-0.000687***	0.0000751	-0.000208*	-0.000418***	-0.000511***
	(0.000139)	(0.0000619)	(0.0000748)	(0.0000848)	(0.0000380)	(0.0000701)
Index	1.147***	-0.0240	0.714***	0.189***	0.103***	0.198***
	(0.0906)	(0.0245)	(0.0554)	(0.0436)	(0.0250)	(0.0323)
Constant	1.161***	-1.052***	3.376***	0.708***	1.550***	1.120***
	(0.208)	(0.0964)	(0.122)	(0.139)	(0.0584)	(0.108)
select						
Female	-0.670***	-0.290***	-0.834***	-0.510***	-0.523***	-0.670***
	(0.0225)	(0.0282)	(0.0172)	(0.0228)	(0.0196)	(0.0303)
Married	-0.0942***	-0.651***	-0.130***	0.580***	-0.0510***	0.0821**
	(0.0159)	(0.0320)	(0.0109)	(0.0269)	(0.00538)	(0.0252)
Minority	0.0400*	0.106	0.259***	0.0423	-0.0764***	-0.0373
	(0.0186)	(0.0633)	(0.0182)	(0.0541)	(0.0120)	(0.0383)
TotalChildren	-0.0482***	-1.144***	-0.0262***	-1.234***	0.0730***	-0.437***
	(0.0124)	(0.0330)	(0.00610)	(0.0322)	(0.0159)	(0.0229)
Education(Years)	0.0432***	0.0554***	0.0418***	0.0884***	0.0676***	0.0443***
	(0.00312)	(0.00442)	(0.00253)	(0.00370)	(0.00374)	(0.00452)
Age	-0.0115***	-0.0648***	-0.00993***	-0.0552***	-0.0341***	-0.0733***
	(0.000922)	(0.00138)	(0.000657)	(0.00122)	(0.000982)	(0.00143)
Constant	-0.446***	3.933***	-0.173**	1.068***	1.067***	3.752***
	(0.0656)	(0.159)	(0.0532)	(0.0996)	(0.0640)	(0.114)
athrho						
Constant	-1.681***	-0.187***	-1.992***	-0.107***	-1.282***	-0.340***
	(0.0481)	(0.0496)	(0.0513)	(0.0297)	(0.0248)	(0.0514)
lnsigma						
Constant	0.880***	-0.546***	0.835***	-0.249***	-0.243***	-0.440***
	(0.0216)	(0.00780)	(0.0127)	(0.00760)	(0.0107)	(0.0105)
Observations	21526	12824	24953	15779	19665	11181
R^2						

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 6.8: Decomposed OLS estimates on Log Wages

	(1) 1995 Rural	(2) 1995 Urban	(3) 2002 Rural	(4) 2002 Urban	(5) 2007 Rural	(6) 2007 Urban
Female	-252.1***	-787.2***	-957.0***	-2140.8***	-4328.3***	-7487.6***
	(27.45)	(78.46)	(31.54)	(173.9)	(388.9)	(652.5)
Age	19.48***	291.4***	113.4***	426.4***	626.6***	1516.0***
	(5.847)	(25.28)	(3.035)	(61.30)	(87.24)	(226.1)
Age2	-0.285***	-2.529***	-1.402***	-3.416***	-9.364***	-17.82***
	(0.0727)	(0.318)	(0.0398)	(0.758)	(1.159)	(2.816)
HS	-12.15	745.4***	509.7***	2514.2***	374.8	3091.4***
	(77.90)	(104.9)	(55.69)	(218.0)	(742.7)	(863.1)
College	-133.0	1550.9***	1287.5***	6637.0***	1574.6**	14303.1***
	(359.6)	(89.51)	(76.67)	(227.2)	(525.8)	(873.0)
Enrollment Ratio	28.24**	18.02	15.72	121.7	-86.33	-874.1***
	(9.896)	(21.35)	(11.18)	(64.03)	(126.8)	(162.6)
GDP per capita	57.41***	217.2***	199.8***	650.7***	536.2***	434.2***
	(5.138)	(12.55)	(5.287)	(21.94)	(45.81)	(36.94)
Constant	-13.27	-2284.8***	-91.31	-4021.9**	9181.4***	-1026.3
	(125.7)	(517.3)	(88.69)	(1277.0)	(1828.9)	(4571.6)
Observations	14649	9470	30227	8836	8784	6783
R^2	0.015	0.132	0.133	0.212	0.037	0.095

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 6.9: Decomposed Heckman Two-Step Estimation on Log Wages

	1995 Rural	1995 Urban	2002 Rural	2002 Urban	2007 Rural	2007 Urban
lnwage						
Female	1.200***	-0.126***	1.355***	-0.137***	-0.0510**	-0.240***
	(0.0747)	(0.0122)	(0.0532)	(0.0171)	(0.0157)	(0.0175)
HS	0.222**	0.157***	0.107**	0.165***	-0.0497*	0.166***
	(0.0818)	(0.0160)	(0.0402)	(0.0206)	(0.0234)	(0.0200)
College	0.654**	0.290***	0.289***	0.381***	-0.0570**	0.571***
	(0.226)	(0.0142)	(0.0544)	(0.0222)	(0.0180)	(0.0207)
Age	0.00701	0.0713***	-0.0122*	0.0374***	0.0378***	0.0497***
	(0.0106)	(0.00476)	(0.00622)	(0.00660)	(0.00292)	(0.00533)
Age2	-0.00000969	-0.000641***	0.000187*	-0.000332***	-0.000414***	-0.000555***
	(0.000136)	(0.0000612)	(0.0000744)	(0.0000822)	(0.0000375)	(0.0000683)
GDP per capita	0.0850***	0.0341***	0.0974***	0.0441***	0.0229***	0.0155***
	(0.00460)	(0.00188)	(0.00407)	(0.00207)	(0.00148)	(0.000866)
Enrollment Ratio	-0.0679***	-0.0105**	-0.0341***	0.00557	0.00151	-0.0260***
	(0.0147)	(0.00322)	(0.00847)	(0.00607)	(0.00428)	(0.00378)
Constant	1.553***	-1.070***	3.698***	0.359**	1.540***	1.074***
	(0.215)	(0.0969)	(0.129)	(0.137)	(0.0605)	(0.105)
select						
Female	-0.669***	-0.289***	-0.835***	-0.510***	-0.527***	-0.671***
	(0.0226)	(0.0281)	(0.0173)	(0.0228)	(0.0196)	(0.0303)
Married	-0.0909***	-0.643***	-0.131***	0.580***	-0.0511***	0.0842***
	(0.0167)	(0.0321)	(0.0114)	(0.0269)	(0.00537)	(0.0252)
Minority	0.0859***	0.100	0.261***	0.0486	-0.0709***	-0.0363
	(0.0203)	(0.0628)	(0.0190)	(0.0540)	(0.0119)	(0.0383)
TotalChildren	-0.0522***	-1.143***	-0.0124*	-1.237***	0.0828***	-0.436***
	(0.0130)	(0.0329)	(0.00630)	(0.0322)	(0.0158)	(0.0229)
Education(Years)	0.0452***	0.0552***	0.0409***	0.0880***	0.0637***	0.0443***
	(0.00324)	(0.00441)	(0.00263)	(0.00370)	(0.00375)	(0.00452)
Age	-0.0116***	-0.0647***	-0.0104***	-0.0553***	-0.0342***	-0.0733***
	(0.000936)	(0.00138)	(0.000667)	(0.00122)	(0.000979)	(0.00143)
Constant	-0.543***	3.929***	-0.166**	1.069***	1.094***	3.749***
	(0.0686)	(0.158)	(0.0546)	(0.0994)	(0.0638)	(0.114)
athrho						
Constant	-1.530***	-0.251***	-1.890***	-0.140***	-1.294***	-0.318***
	(0.0504)	(0.0519)	(0.0605)	(0.0284)	(0.0249)	(0.0502)
lnsigma						
Constant	0.793***	-0.564***	0.782***	-0.274***	-0.253***	-0.469***
	(0.0236)	(0.00820)	(0.0148)	(0.00768)	(0.0107)	(0.0103)
Observations	21526	12824	24953	15779	19665	11181
R^2						

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

BIBLIOGRAPHY

Annual Data on Industries, National Bureau of Statistics of China, http://www.stats.gov.c accessed July 2, 2017

Artuç, E., Chaudhuri, S. and McLaren, J. (2008). "Delay and Dynamics In Labor Market Adjustment: Simulation Results", *Journal of International Economics*, vol 75

Berdard, K. (2001). "Human Capital Versus Signaling Models: University Access and High School Dropouts",*Journal of Political Economy*, Vol 109, no. 4

Berdard, K. and Ferrall, C. (2003). "Wage and Test Score Dispersion: Some International Evidence", *Economics of Education Review*, vol 22

Caponi, V., and Plesca, M. (2009). "Post-Secondary Education in Canada: Can Ability Bias Explain the Earnings Gap Between College and University Graduates?" , *The Canadian Journal of Economics*, vol. 42, no. 3

Chen, S., and Ravallion, M. (2004). "Welfare Impacts of China's Accession to the World Trade Organization." , *The World Bank Economic Review*, vol. 18, no. 1

Chinese Household Income Project, China Institute for Income Distribution,http://www.ciidbnu.org/chip/index.asp, 1988-2013.

County Level Economic database, China Data Online, http://chinadataonline.org/, accessed July 10, 2017

County Level education database, China Data Online, http://chinadataonline.org/, accessed July 10, 2017

Ianchovichina, E. and Martin, W.(2004). "Impacts of China's Accession to the World Trade Organization." , *The World Bank Economic Review*, vol. 18, no. 1

Hakobyan, S., McLaren, J.(2016). "Looking For Local Labor Market Effects of NAFTA", *The Review of Economics and Statistics*

Hanson, G. (2005). "Globalization, Labor Income and poverty in Mexico", National Bureau of Economic Research Working Paper

Heckman, J. (1979). "Sample Selection Bias as a Specification Error." ,*Econometrica*, vol. 47, no. 1

Helpman, E. and O. Itskhoki. and Redding, S.(2010) "Unequal Effects of Trade on Workers With Different Abilities", *Journal of the European Economic Association*, vol. 8, no. 2/3

Helpman, E., Isthoki, O.(2015). "Trade Liberalization and Labor Market Dynamics with Heterogeneous Firms", working paper, http://www.princeton.edu/ itskhoki/papers/TradeLMDynamics.pdf

Kennan, J., and Walker, J.(2011). "The Effect of Expected Income on Individual Migration Decisions", *Econometrica*, vol. 79, no. 1

Krugman, P. (1980). "Scale Economies, Product Differentiation, and the Pattern of Trade.", *The American Economic Review*, vol. 70, no. 5

Lardy, N. (2014). "Rise of the Private Sector", *Markets Over Mao*, Peterson Institute for International Economics

Melitz, M. (2003). “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity.” , *Econometrica*, vol. 71, no. 6

Ministry of Education Annual Snap Shot, Ministry of Education, http://en.moe.gov.cn/, accessed July 5, 2017

NBSC Annual statistics summary, National Bureau of Statistics, http://www.stats.gov.cn, accessed June 5, 2017

Ravi, K., Wang, Y., and Zhang X. (2017). "The Great Chinese Inequality Turnaround." , Bank of Finland Institute for Economies in Transition, Discussion Papers

"Regional minimum wage levels", Ministry of Human Resources and Social Security, http://www.mohrss.gov.cn, accessed July 3, 2017

Samuelson, P. (1971). “Ohlin Was Right.” , *The Swedish Journal of Economics*, vol. 73, no. 4

Topalova, P. (2004). "Factor Immobility and Regional Effects of Trade Liberalization: Evidence from India". Massachusetts Institute of Technology, Department of Economics

Topalova, P. (2007). "Trade Liberalization, Poverty, and Inequality Evidence from Indian Districts", *Globalization and Poverty*, Ed. Ann Harrison, University of Chicago Press

Vaillancourt, F. (1995). “The Private and Total Returns to Education in Canada, 1985.”, *The Canadian Journal of Economics* / Revue Canadienne D’Economique, vol. 28, no. 3

WTO Tariff Data, "http://data.worldbank.org/indicator/TM.TAX.MRCH.WM.AR.ZS", accessed July 25, 2017