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The Contribution of Supply and Demand Shifts to Earnings Inequality in Urban China

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Abstract

This paper examines the degree to which supply and demand shift across skill groups contributed to the earnings inequality increase in urban China from 1988 to 2002. Product demand shift contributed to an equalizing of earnings distribution in urban China from 1988 to 1995 by increasing the relative product for the low educated. However, it contributed to enlarging inequality from 1995 to 2002 by increasing the relative demand for the highly educated. Relative demand was continuously higher for workers in the coastal region and contributed to a raising of interregional inequality. Supply shift contributed essentially nothing or contributed only slightly to a reduction in inequality. Remaining factors, the largest disequalizer, may contain skill-biased technological and institutional changes, and unobserved supply shift effects due to increasing numbers of migrant workers.

Keywords: urban China, earnings inequality, inequality decomposition
JEL classification: D31, J31

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October 2008 (Revised in June 2009)

Abstract

This paper examines the degree to which supply and demand shift across skill groups contributed to the earnings inequality increase in urban China from 1988 to 2002. Product demand shift contributed to an equalizing of earnings distribution in urban China from 1988 to 1995 by increasing the relative demand for the low educated. However, it contributed to enlarging inequality from 1995 to 2002 by increasing the relative demand for the highly educated. Relative demand was continuously higher for workers in the coastal region and contributed to a raising of interregional inequality. Supply shift contributed essentially nothing or contributed only slightly to a reduction in inequality. Remaining factors, the largest disequalizer, may contain skill-biased technological and institutional changes, and unobserved supply shift effects due to increasing numbers of migrant workers.

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1. Introduction

Asuyama (2008) showed how the causes of earnings inequality changed between the two periods 1988-1995 and 1995-2002 by primarily reflecting labor-related institutional reform in China. Since my analysis in this paper is an extension of Asuyama (2008) and uses the same dataset, I first reproduce here a summary of the findings in Asuyama (2008). By examining the individual samples from 1988, 1995, and 2002 of urban Chinese residents, drawn from the survey called the Chinese Household Income Project (CHIP), Asuyama (2008) first confirmed that earnings inequality in urban China continuously increased from 1988 to 2002, even when adjusted for regional price differences (RPD). The Gini coefficient based on RPD-adjusted earnings was 0.233 in 1988, 0.278 in 1995, and 0.330 in 2002, respectively. The paper then reveals how the causes of earnings inequality changed between the two periods 1988-1995 and 1995-2002 by reflecting labor-related institutional reform in China. Contrary to the situation from 1988 to 1995, between 1995 and 2002, employment status (permanent or temporary worker, etc.) became the largest disequalizer, and the decline of inter-provincial inequality contributed to a reduction in the overall earnings inequality. Individual ability, represented by education and occupation, received much greater rewards. Throughout the period from 1988 to 2002, a large part of the explained inequality increase was due to price change (changes in the valuation of individual attributes) and not due to quantity change (changes in the composition of individual attributes). Table 1 and Table 2, drawn from Tables 5-7 of Asuyama (2008) summarize these inequality decomposition results.

Asuyama (2008) argued that the above decomposition results mainly reflected labor-related institutional reform in China. However, since this reform introduced market mechanisms into the Chinese labor system, it is also necessary to examine how much supply and demand shifts contributed to the earnings inequality increase in urban China, in addition to examining institutional factors. It is possible that widening earnings differentials among education groups is due to the relative demand increase for highly educated workers, as seen in the US. Also, supply and demand shift may have contributed to the changes in inter-provincial and intra-provincial inequality.

Numerous studies have been carried out on the causes of the earnings inequality increase in the US after 1980. There are three major explanations for the causes of rising overall inequality (or the growing educational wage differentials, which is the most important factor in the rising overall inequality). Katz and Autor (1999) label these the SDI (supply-demand-institution) explanation or framework. First, the explanation from the supply-side is that the relative supply increase in highly educated workers is considered to have contributed to a suppression of the relative wage increase to highly educated workers and thus to a reduction in inequality. However, the shrinking cohort size of the highly educated and increased numbers of unskilled immigrants may have contributed to an increase in inequality. Second, the demand increase for highly educated workers, which exceeded the supply increase of those workers, was considered one of the major factors in the rise in the relative wage of the highly educated. Product demand shift due to the increased imports of goods produced by unskilled labor and skill-biased technological change, such as the increased use of computers in workplaces, were considered the two major causes of the relative demand increase for the highly educated. Such relative demand increase for the highly educated led to the increase in the educational wage differentials. Third, institutional factors such as the decline in unionization and real minimum wage rates were also considered to be contributors to the increase in the educational earnings differentials.

There are almost no studies which estimate the degree to which supply and demand factors contributed to earnings inequality in urban China. Although, as in the US, a rising return to education in urban China has also been observed by many studies, the causes have not yet been fully investigated. For example, Zhang, Zhao, Park, and Song (2005) showed that the rising return to education in urban China from 1988 to 2001 was strongly associated with the market-oriented reform of labor market institutions. However, they also admitted that "additional work is necessary to evaluate the contributions of skill-biased technical change and globalization to the rising returns to skill in China." One exception is Liu, Park, and Zhao (2007), who in an "incomplete and preliminary" paper directly applied the method of Bound and Johnson (1992) to decompose wage differentials between education groups in urban China from 1990 to 2001 into five effects: 1) changes in industrial wage rents, 2) supply shift, 3) product demand shift, 4) general technological change, and 5) a residual factor. Following the method of Bound and Johnson (1992), they estimated these five effects by constructing 24 sex-education-experience skill groups.[1]

In this paper, I examine the degree to which supply and demand shift across skill groups contributed to the earnings inequality increase in urban China from 1988 to 2002. The major differences in my analysis from that of Liu, Park, and Zhao (2007) are as follows: First, instead of decomposing the earnings differentials between education groups as they did, I aim to measure how much supply and demand shifts across skill groups contributed to the inequality increase in the entire earnings distribution in urban China. Second, in order to take into account the existence of labor market segmentation by province in urban China, I construct skill groups by region (whether coastal or inland), education, and experience, using region instead of sex. Third, I also incorporate the supply and demand shift effects across skill groups into the inequality decomposition result presented in Asuyama (2008). As a result, I am able to present a more comprehensive picture of the causes of earnings inequality in urban China.

This paper is organized as follows: Section 2 briefly explains the dataset used in my analysis. Section 3 describes the empirical strategy by which the supply and demand shift effects are estimated. Section 4 presents the estimation results. It shows the degree to which supply and demand shift across skill groups contributed to earnings inequality in urban China. Section 4 also decomposes the total earnings inequality into supply and demand shift effects and other factors. Section 5 discusses the interpretation of the results. Finally, Section 6 summarizes the findings and mentions the limitations of my analysis.

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[1] After completing my analysis, I found their revised paper, Liu et al. (2008). However, their main findings are not changed largely except that they newly found that the supply shifts contributed to enlarging the wage differentials between senior and junior high school graduates in the late 1990s.

2. Data

The same dataset as used in Asuyama (2008) is used here. It contains individual samples of urban Chinese residents from 1988, 1995, and 2002, drawn from the survey called the Chinese Household Income Project (CHIP) (Griffin & Zhao, 1993; Riskin, Zhao, & Li, 2000; RCIDP).[2] My sample includes only working or employed individuals who are age 16 or above, are reporting positive earnings, and are living in the urban areas of ten provinces, namely Beijing, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Guangdong, Yunnan, and Gansu. The sample largely excludes rural-urban migrants who have rural registration (*hukou*) but are living in urban areas.[3] Earnings are defined as annual wage, which includes bonuses and subsidies from the primary work unit. They are adjusted for regional price differences (RPD) based on the 1988 Beijing price level. For more information on the dataset, including the treatment of missing values and summary statistics, refer to Section 2 of Asuyama (2008).

3. Empirical Strategy

I applied the methods used in DiNardo, Fortin, and Lemieux (1996) and Bound and Johnson (1992) in order to estimate the effects of supply and demand (S&D) shifts across different skill groups on their earnings change in the two periods 1988 to 1995 and 1995 to 2002.[4] I briefly explain the estimation method below. For more detail, refer to the two papers

[2] I acknowledge the Research Center for Income Distribution and Poverty (RCIDP), Beijing Normal University (BNU), and the Inter-university Consortium for Political and Social Research (ICPSR), which distribute the CHIP datasets and who allowed me to use the datasets for my analysis.

[3] Only in the 2002 CHIP questionnaire, there is a question about *hukou* status. The result reveals that some urban residents actually have rural *hukou*. According to Appleton and Song (2008), they were included “because of their purchase of urban temporary status”. In fact, my CHIP 2002 sample includes 83 workers having rural *hukou*. However, the proportion of them is very small (1.0%) and does not affect the essence of this paper. Using the sample excluding those rural-*hukou* workers does not change the inequality indices and regression-based decomposition results largely. In addition, the distribution of skill and industry groups of the sample excluding rural-*hukou* workers is not statistically different from the one including those workers.

[4] DiNardo et al. (1996) decomposed the changes in male and female wage inequality in the US into the effects of 1) minimum wage, 2) unionization, 3) other individual attributes (education, experience, race, SMSA, occupation, industry etc.), 4) supply and product demand, and 5) residual factors which include skill-biased technological change. In order to extract the supply and product demand shift effect, they applied the method developed by Bound and Johnson (1992) who decomposed the changes in wage

mentioned. Liu, Park, and Zhao (2007) also explain the method of Bound and Johnson (1992) in detail. In particular, regarding the assumptions of the model and derivation of equations, see the Appendix of Bound and Johnson (1992).[5]

3.1 Estimation steps for S&D shift effects on earnings inequality change

Step 1. Main model equation and the assumptions of the model

First, all *N* workers in the sample at time *T* (in my case, 1988, 1995, or 2002) are divided into *I*J* cells, where *I* indicates the number of skill groups defined by sex-education-experience categories in the literature, and region-education-experience categories in my analysis as mentioned below, and *J* indicates the number of industries.

The main equation of the model is the equation (1) below, which shows that the change in competitive relative wage of each skill group during time period *t* (in this case, within the periods 1988 to 1995 or 1995 to 2002) can be decomposed into 1) the supply shift effect (the first term), 2) the product demand shift effect (the second term), and 3) the remaining factor, which theoretically represents a general technological change effect (the third term). Technological changes affect the productivity of a certain skill group, and thus change the price (i.e. wage) paid for that group.

$$\Delta \ln W_{i,t} = -(1/\sigma)SUP_{i,t} + (1/\sigma)DEM_{i,t} + (1-1/\sigma)\Delta \ln b_{i,t} + u_{i,t} \qquad (1)$$

where subscripts *i* and *t* represent skill group-*i* and time period *t* (1988-1995, or 1995-2002), respectively. $\Delta \ln W_{i,t}$ is the change in competitive relative wage (estimated in step 2), $SUP_{i,t}$ is the supply shift index (estimated in step 3), $DEM_{i,t}$ is the product demand shift index (estimated in step 4), $\Delta \ln b_{i,t}$ represents the technological efficiency, σ is the elasticity of intrafactor substitution, which is assumed to be constant across skill groups and industries over

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differentials between skill groups into the effects of 1) industry rents, 2) supply, 3) product demand, and 4) specific and general technological change. Since I decompose the entire earnings distribution as in DiNardo et al. (1996), I primarily follow the method of DiNardo et al. (1996) and then refer to the method of Bound and Johnson (1992).

[5] I am deeply appreciative of the helpful information concerning the estimation procedure received from Professor DiNardo and Professor Liu.

time, and $u_{i,t}$ is a random error term.

As explained in Bound and Johnson (1992) and Liu, Park, and Zhao (2007), there are six major assumptions for this model: 1) the production function is assumed to be of the constant elasticity of substitution (CES) form as below. In other words, the degree of substitutability between any pairs of skill groups is assumed to be the same across industries and over time.

$$Q_j = a_j [\sum_i \delta_{ij} (b_{ij} N_{ij})^{(\sigma-1)/\sigma}]^{\sigma/(\sigma-1)}$$

where Q_j is output of industry *j*, a_j is a parameter representing the technological efficiency of industry *j*, δ_{ij} is a distribution parameter, σ is the elasticity of intrafactor substitution, b_{ij} is an index of the technological efficiency of group-*i* workers in industry *j*, and N_{ij} is the employment (number of observations) of group-*i* workers in industry *j*. 2) The relative demand for the output of each industry is a function of its relative price and an exogenous shift parameter which reflects consumers tastes, and so on. 3) Employment levels in each cell (N_{ij}) are determined by equating the marginal revenue products of the *I* labor inputs with their competitive wage rates. 4) The economy is at full employment, that is, the total labor supply is equal to the total labor demand and thus the competitive wage may be freely adjusted. 5) The labor supply is exogenous or pre-determined and does not depend on relative wages. 6) Each skill group is considered to be equipped with the same labor inputs. It should be kept in mind that these assumptions may not hold, especially in China where the competitive labor market is under construction and seems to be more segmented than in the US. However, it is still interesting to apply this model (alleviating the incomplete labor market problem by taking into account the regional supply and demand differences) to see what result is obtained, given the fact that that there are currently almost no studies which estimate the supply and demand shift effects on inequality in urban China.

Step 2. Estimation of competitive cell mean relative earnings change $\Delta \ln W_{i,t}$

In order to estimate the competitive cell mean relative earnings change for each skill group-*i*, it is necessary to remove the earnings changes due to the changes in individual attributes and changes in industry-specific earnings premium. Thus, following DiNardo, Fortin, and Lemieux (1996), I first ran an OLS regression of log earnings (adjusted for regional price differences) on individual attributes (sex, minority status, Communist Party membership, years of experience, years of experience squared, education level, ownership, occupation, industry, employment status, and province) and skill group dummies for each year separately. Then, for each skill group in each year, I computed predicted earnings $\ln \hat{W}_{i,95}$ and $\ln \hat{W}_{i,88}$ for a representative worker who possesses the mean cell attributes ($\overline{Z}_{i1\_88}$) of the base period (1988) and the average industry affiliation of the entire sample ($\overline{Z}_{2\_88}$) of 1988. The estimated competitive cell mean relative earnings change during time period *t1* (1988-1995) for each skill group $\Delta \ln W_{i,t1}$ then becomes

$$\Delta \ln W_{i,t1} = \Delta \ln W_{i,t1}^{'} - \sum_i \Delta \ln W_{i,t1}^{'} \phi_{i,t1}$$

where $\Delta \ln W_{i,t1}^{'} = \ln \hat{W}_{i,95}(\overline{Z}_{1i\_88}, \overline{Z}_{2\_88}) - \ln \hat{W}_{i,88}(\overline{Z}_{1i\_88}, \overline{Z}_{2\_88})$, and

$\phi_{i,t1} = Ni / N$ is the proportion of each skill group to the total employment in 1988.

This $\Delta \ln W_{i,t1}$ represents the relative earnings change of a representative person of skill group-i from 1988 to 1995, assuming that his or her attributes and industry affiliation had not changed since 1988 and the industry affiliation was common across all skill groups. $\Delta \ln W_{i,t1}$ must then be explained by the change in the relative supply of skill groups, change in the relative demand for skill groups across industries, and technological change (or changes in the productivity of skill groups), as expressed in equation (1).[6]

The competitive relative earnings change during time period *t2* (1995-2002) for each skill group $\Delta \ln W_{i,t2}$ is estimated similarly.

Step 3. Computation of supply shift index $SUP_{i,t}$

SUP_i for period *t1* (1988-1995) is merely the change in the log of group-*i*'s proportion

[6] As discussed below, changes in the price system for skills or institutional changes may be another possible explanation.

to the total labor supply.

$$SUP_{i,t1} = \Delta\ln(\phi_i)_{t1} = \ln(\phi_{i95}) - \ln(\phi_{i88})$$

where $\phi_i = N_i / N$ is the proportion of total group-*i* employment (or observations N_i) to total employment (N).

Similarly, SUP_i for period *t2* (1995-2002) is computed.

Step 4. Estimation of product demand shift index $DEM_{i,t}$

DEM_i is estimated by the following equation (subscript *t* is omitted).

$$DEM_i = \sum_j \Delta(\ln x_j)\phi_{ij}$$

where $\phi_{ij} = N_{ij} / N_i$ is the proportion of total employment in cell *ij* (N_{ij}) to total employment of group-*i* (N_i). x_j is the relative demand for the output of industry *j*, and $\Delta(\ln x_j)$, which is the relative product demand shift for industry *j*, is estimated by the following OLS regression.

$$\Delta(\ln\phi_{ij}) = (1-\phi_{ij})\Delta(\ln x_j) - \sum_{k\neq j}\phi_{ik}\Delta(\ln x_k) + (\sigma-1)\Delta\ln(b_{ij}/b_i)$$

which can be rewritten in matrix form as below.

$$\begin{bmatrix} \Delta(\ln\phi_{11}) \\ \Delta(\ln\phi_{12}) \\ \vdots \\ \Delta(\ln\phi_{IJ}) \end{bmatrix} = \begin{bmatrix} 1-\phi_{11} & -\phi_{12} & \cdots & -\phi_{1J} \\ -\phi_{11} & 1-\phi_{12} & \cdots & -\phi_{1J} \\ \vdots & \vdots & & \vdots \\ -\phi_{I1} & -\phi_{I2} & \cdots & 1-\phi_{IJ} \end{bmatrix} \begin{bmatrix} \Delta\ln(x_1) \\ \Delta\ln(x_2) \\ \vdots \\ \Delta\ln(x_J) \end{bmatrix} + \begin{bmatrix} \Delta[\ln(b_{11}/b_1)] \\ \Delta[\ln(b_{12}/b_1)] \\ \vdots \\ \Delta[\ln(b_{IJ}/b_I)] \end{bmatrix}$$

where $\Delta(\ln\phi_{ij})$ is the change in the log of $\phi_{ij} = N_{ij} / N_i$, and $\Delta\ln(b_{ij}/b_i)$ is the relative technological change for workers in cell *ij* compared to the average of group-*i* workers. For the derivation of this equation, refer to the Appendix of Bound and Johnson (1992).

If there is no information about the pattern of industry-specific technological change, the last term $(\sigma-1)\Delta\ln(b_{ij}/b_i)$ can be treated as an error term (Bound and Johnson, 1992). Since $\Delta(\ln\phi_{ij})$, $(1-\phi_{ij})$, and ϕ_{ik} can be computed from the raw data, $\Delta(\ln x_j)$ can be estimated for all *j*'s by regressing $\Delta(\ln\phi_{ij})$ on $(1-\phi_{ij})$, and ϕ_{ik}, if we treat the last term as an error and add a constraint that the weighted average of relative demand shift $\Delta(\ln x_j)$ is equal to zero (the weight is the proportion of each industry's employment to total employment (N_j / N) in the base period). In this analysis, it is assumed that there is no industry-specific technological change and the last term is treated as an error.[7]

In this way, DEM_i is computed for both periods, 1988-1995 (*t1*) and 1995-2002 (*t2*).

Step 5. Decomposing competitive cell mean earnings change into supply shift effect, product demand shift effect, and the remaining factor including general technological change effect

In the previous steps, we have already estimated $\Delta \ln W_{i,t}$, $SUP_{i,t}$, and $DEM_{i,t}$ for both 1988-1995 (*t1*) and 1995-2002 (*t2*). Following equation (1), the competitive cell mean relative earnings change can be decomposed into 1) the supply shift effect, 2) the product demand shift effect, and 3) the remaining factor, which theoretically represents the general technological change effect, by regressing $\Delta \ln W_{i,t}$ on $SUP_{i,t}$ and $DEM_{i,t}$ if we can treat the last term as an error. However, it is possible that the last term $(1-1/\sigma)\Delta \ln b_{i,t}$, which represents general technological change, is correlated with supply and product demand shifts. Such correlation generates a biased estimate, when we treat $(1-1/\sigma)\Delta \ln b_{i,t}$ as an error. In order to eliminate the bias, it is necessary to fit equation (1) in second differences (1995-2002 change minus 1988-1995 change), as DiNardo, Fortin, and Lemieux (1996) and Bound and Johnson (1992) have shown. By fitting equation (1) in second differences, we get:

$$
\begin{aligned}
&(\Delta \ln W_{i,t2} - \Delta \ln W_{i,t1}) \\
&= -(1/\sigma)(SUP_{i,t2} - SUP_{i,t1}) + (1/\sigma)(DEM_{i,t2} - DEM_{i,t1}) \\
&\quad + (1-1/\sigma)(\Delta \ln b_{i,t2} - \Delta \ln b_{i,t1}) + (u_{i,t2} - u_{i,t1}) \qquad (2)
\end{aligned}
$$

where *t1* and *t2* indicate the periods from 1988 to 1995 and 1995 to 2002, respectively.

If we can assume that the pace of general technological change for each skill group, $(\Delta \ln b_{i,t2} - \Delta \ln b_{i,t1})$ is identical across all skill groups (i.e. $(1-1/\sigma)(\Delta \ln b_{i,t2} - \Delta \ln b_{i,t1}) = A_i = A$), the last term becomes a constant term, and we are then able to obtain unbiased coefficients for SUP_i and DEM_i. Although the model assumes

[7] I have followed DiNardo, Fortin, and Lemieux (1996) in treating the last term as an error. Liu, Park, and Zhao (2007) also examined the existence of industry-specific technological change in urban China from 1990 to 2001, but found no evidence for it.

that the absolute values of the coefficients for SUP_i and DEM_i are equal ($=1/\sigma$) and Bound and Johnson (1992) maintained this assumption, I have followed DiNardo et al. (1996) and allowed the coefficients to differ.

In order to take into account the relative population size of each skill group, I ran a weighted least squares (WLS) regression in second differences. All variables in the regression equation were weighted by $\sqrt{\phi_{i,95}}$, where $\phi_{i,95}$ is the proportion of each skill group to the total employment (N_i / N) in 1995.

In order to check the above assumption that the pace of general technological change is identical across all skill groups (i.e. $A_i = A$), I also ran a regression including dummies for region, education group, and experience group. If the coefficients for those dummies are significantly different from zero, it indicates that the pace of technological change is different across groups (i.e. $A_i = A_0 + A_{1i}$, where A_0 is common for all skill groups and A_{1i} represents a group-specific speed of technological change). In that case, we can express the above equation (2) as:

$$\begin{aligned}&(\Delta \ln W_{i,t2} - \Delta \ln W_{i,t1})\\ &= -(1/\sigma)(SUP_{i,t2} - SUP_{i,t1}) + (1/\sigma)(DEM_{i,t2} - DEM_{i,t1})\\ &\quad + (A_0 + A_{1i}) + (u_{i,t2} - u_{i,t1}) \qquad (3)\end{aligned}$$

where $(A_0 + A_{1i}) = (1 - 1/\sigma)(\Delta \ln b_{i,t2} - \Delta \ln b_{i,t1})$

By fitting equation (3) with WLS, coefficients for SUP_i , DEM_i and each demographic dummy A_{1i}, and a constant term A_0 can be obtained. Using the coefficients for SUP_i and DEM_i first, the competitive cell mean relative earnings change due to 1) the supply shift ($-(1/\sigma)SUP_{i,t}$), and 2) the product demand shift ($(1/\sigma)DEM_{i,t}$), are predicted for each period (*t1*: 1988-1995 and *t2*: 1995-2002).[8]

Following Bound and Johnson (1992), the cell mean relative earnings change due to general technological change can be estimated by computing the average of the residuals

[8] As noted above, in the actual estimation process, I allowed the absolute values of the coefficients for SUPi and DEMi to differ.

obtained after removing supply and product demand shift effects over the two periods.

Since $(1-1/\sigma)\Delta\ln b_{i,t2} = (1-1/\sigma)\Delta\ln b_{i,t1} + (A_0 + A_{1i})$,

$$[(1-1/\sigma)\Delta\ln b_{i,t1} + u_{i,t1}] + [(1-1/\sigma)\Delta\ln b_{i,t2} + u_{i,t2}]$$
$$= [2(1-1/\sigma)\Delta\ln b_{i,t1} + (A_0 + A_{1i}) + u_{i,t1} + u_{i,t2}]$$
$$= [\Delta\ln W_{i,t1} + (1/\sigma)SUP_{i,t1} - (1/\sigma)DEM_{i,t1}] + [\Delta\ln W_{i,t2} + (1/\sigma)SUP_{i,t2} - (1/\sigma)DEM_{i,t2}]$$
$$= [residual, t1] + [residual, t2]$$

Thus, assuming $u_{i,t1}$ and $u_{i,t2}$ are negligible, the competitive cell mean earnings change due to the remaining factor, representing general technological change for period *t1* and *t2*, are obtained as follows:

$$(1-1/\sigma)\Delta\ln b_{i,t1} \approx 1/2\{[residual, t1] + [residual, t2] - (A_0 + A_{1i})\}$$
$$(1-1/\sigma)\Delta\ln b_{i,t2} = (1-1/\sigma)\Delta\ln b_{i,t1} + (A_0 + A_{1i})$$

If there is no significant evidence for a different pace of technological change across skill groups, the above equations are calculated by replacing $(A_0 + A_{1i})$ with A, which is simply the constant term obtained from the regressing equation (2).

Step 6. Calculating the contribution of supply shift, product demand shift, and general technological change to the earnings inequality change

First, the counterfactual earnings distribution in 1995, with 1) no supply shift, 2) no product demand shift, and 3) no general technological change, and 4) none of these three shifts since 1988, is constructed by subtracting the predicted cell mean relative earnings change due to each shift from the actual cell mean earnings for 1995 for each skill group.

Counterfactual earnings distribution in 1995 with 1) no supply shift since 1988

$$f(\ln W)_{noS} = f(\ln W \mid t = 95, S = 88, D, G = 95)$$
$$= f(\ln W - \Delta\ln Ws_i \mid t = 95, S, D, G = 95)$$

where $f(\ln W)_{noS} = f(\ln W \mid t = 95, S = 88, D, G = 95)$: The counterfactual earnings distribution in 1995 with no supply shift since 1988,

$f(\ln W \mid t = 95, S, D, G = 95)$: The actual earnings distribution in 1995, and

$\Delta \ln Ws_i$: The predicted cell mean relative earnings change due to the supply shift for skill group-*i*, which is estimated in step 5.

Counterfactual earnings distribution in 1995 with 2) no product demand shift since 1988

$$f(\ln W)_{noD} = f(\ln W \mid t = 95, D = 88, S, G = 95)$$
$$= f(\ln W - \Delta \ln Wd_i \mid t = 95, S, D, G = 95)$$

where $f(\ln W)_{noD} = f(\ln W \mid t = 95, D = 88, S, G = 95)$: The counterfactual earnings distribution in 1995 with no product demand shift since 1988, and

$\Delta \ln Wd_i$: The predicted cell mean relative earnings change due to product demand shift for skill group-*i*, which is estimated in step 5.

Counterfactual earnings distribution in 1995 with 3) no general technological change since 1988

$$f(\ln W)_{noG} = f(\ln W \mid t = 95, G = 88, D, S = 95)$$
$$= f(\ln W - \Delta \ln Wg_i \mid t = 95, S, D, G = 95)$$

where $f(\ln W)_{noG} = f(\ln W \mid t = 95, G = 88, D, S = 95)$: The counterfactual earnings distribution in 1995 with no general technological change since 1988, and

$\Delta \ln Wg_i$: The predicted cell mean relative earnings change due to general technological change for skill group-*i*, which is estimated in step 5.

Counterfactual earnings distribution in 1995 with 4) none of three shifts since 1988

$$f(\ln W)_{noSDG} = f(\ln W \mid t = 95, S, D, G = 88)$$
$$= f(\ln W - \Delta \ln Ws_i - \Delta \ln Wd_i - \Delta \ln Wg_i \mid t = 95, S, D, G = 95)$$

where $f(\ln W)_{noSDG} = f(\ln W \mid t = 95, S, D, G = 88)$: The counterfactual earnings distribution in 1995 with no supply shift, product demand shift, or general technological change since 1988.

Similarly, four counterfactual earnings distributions in 2002 are constructed, in which the supply, demand, and technological change effect since 1995 are removed.

The contributions of supply shift (S), product demand shift (D), the general technological change (G), and all three shifts in total (SDG) to the RPD-adjusted earnings inequality are then computed by the following equation:

Calculating SDG effect: Individual decomposition

$$S\_effect = [1-(I(.)_{noS} / I(.))]*100(\%)$$

$$D\_effect = [1-(I(.)_{noD} / I(.))]*100(\%)$$

$$G\_effect = [1-(I(.)_{noG} / I(.))]*100(\%)$$

$$SDG\_effect = [1-(I(.)_{noSDG} / I(.))]*100(\%)$$

where S_effect, D_effect, G_effect, and SDG_effect are the contributions of supply shift, product demand shift, general technological change, and all three shifts in total to the inequality (level or its change), respectively. $I(.)_{noS}$, $I(.)_{noD}$, $I(.)_{noG}$, and $I(.)_{noSDG}$ are inequality indices (for inequality level or its change) computed based on the counterfactual earnings distributions $f(\ln W)_{noS}$, $f(\ln W)_{noD}$, $f(\ln W)_{noG}$, and $f(\ln W)_{noSDG}$, respectively. $I(.)$ is an inequality index (for inequality level or its change) computed based on RPD-adjusted earnings.

It should be noted that summing the terms S_effect, D_effect, and G_effect obtained above does not necessarily equal SDG_effect. Alternatively, if we examine the effect of each factor sequentially by using the counterfactual distributions $f(\ln W)_{noS}$, $f(\ln W)_{noSD}$ (counterfactual distribution without supply shift and product demand shift), and $f(\ln W)_{noSDG}$, the sum of S_effect, D_effect, G_effect is equal to SDG_effect (i.e. SDG_effect is exclusively decomposed into S_effect, D_effect, G_effect). However, the magnitude of the effect of each factor changes with the order of decomposition in such a sequential decomposition. In order to avoid this problem, I have chosen to examine the effect of S, D, G individually, but not sequentially, in order to compare the importance of each of *S_, D_, G_effect* in an equal manner.

Step 7. Decomposing the inequality of RPD-adjusted earnings into SDG and other factors

First, following the regression-based decomposition method explained in Fields (2002), the inequality of each counterfactual RPD-adjusted earnings distribution with 1) no supply shift

($f(\ln W)_{noS}$), 2) no product demand shift ($f(\ln W)_{noD}$), 3) no general technological change ($f(\ln W)_{noG}$), and 4) none of the three shifts ($f(\ln W)_{noSDG}$) is decomposed into s_j's: the contribution of institutional and human capital factors (sex, minority status, Communist Party membership, experience, education, ownership, occupation, industry, employment status, province, and residual). Each s_j (the contribution of the *j*'th factor to the inequality level of a certain counterfactual earnings distribution) is computed from the following equation.

$$s_j(\ln Y) = \text{cov}[a_j Z_j, \ln Y]/\sigma^2(\ln Y) = a_j * \sigma(Z_j) * cor[Z_j, \ln Y]/\sigma(\ln Y)$$

where $\ln Y$ is the logarithm of certain counterfactual earnings, Z_j is the *j*'th explanatory variable, and a_j is the estimated coefficient of the *j*'th factor obtained from the regression of $\ln Y_i$ on J's Z_j, σ^2, σ, and cor stand for variance, standard error, and correlation, respectively. $\sum_{j=1}^{J+2} s_j(\ln Y) = 100\%$, and $\sum_{j=1}^{J+1} s_j(\ln Y) = R^2(\ln Y)$, where R^2 stands for R-squared, which represents the overall percentage explained by the explanatory variables (Fields 2002, Equations (8.a-d)).

Using the counterfactual earnings distributions, Π_j (the contribution of the *j*'th factor to the change in an inequality measure between time 1 and time 2) is also calculated as follows:

$$\Pi_j(I(.)) = [s_{j,2} * I(.)_2 - s_{j,1} * I(.)_1]/[I(.)_2 - I(.)_1]$$

where $I(.)_t$ represents an inequality measure calculated at time *t* (*t* = 1 or 2), and $s_{j,t}$ represents the contribution of the *j*'th factor to the inequality level of ln*Y* at time *t*. (Fields 2002, Equation (17.b)). $I(.)_2$ and $s_{j,2}$ are calculated based on the above counterfactual earnings distributions, while $I(.)_1$ and $s_{j,1}$ are based on the actual earnings distributions.

The inequality (level or its change) of the actual RPD-adjusted earnings (=100%) is then decomposed into S_effect, D_effect, and G_effect (%) which are computed in step 6, and the contributions of other factors, each of which are calculated as:

$[(100\% - S\_effect) * s_j(\%)]$, when only S_effect is factored out.

$[(100\% - D\_effect) * s_j(\%)]$, when only D_effect is factored out.

$[(100\% - G\_effect) * s_j(\%)]$, when only G_effect is factored out.

$[(100\% - SDG\_effect) * s_j (\%)]$, when SDG_effect is factored out.

For more details on the regression-based decomposition method, refer to Asuyama (2008) and Fields (2002).

3.2 Construction of skill groups and industry classification

Previous studies (i.e. Bound and Johnson, 1992; DiNardo, Fortin, & Lemieux, 1996; Liu, Park, & Zhao, 2007) constructed approximately 30 skill groups by dividing the entire sample into sex-education-experience groups. In my analysis on urban China, I have used region (whether coastal or inland region) instead of sex, and have constructed 30 region-education-experience skill groups.[9] As mentioned in Asuyama (2008), labor market segmentation by province exists in urban China. Institutional forces such as local government policy together with a different level of demand for labor due to a different pace of economic development may have created this segmentation by province. Since the model explained in this section assumes a competitive labor market, in order to alleviate the violation of the model, I have introduced a regional factor into the construction of skill groups by assuming that regional differences strongly affect the supply and demand (especially demand) of education-experience groups. Since my CHIP sample is too small to construct skill groups by province-education-experience, I have used two regional categories: coastal region and inland region. It is well known that the coastal region has achieved economic development more rapidly than the inland region. Thus, it is expected that demand for labor is higher in the coastal region than in the inland region. Following Kanbur and Zhang (2005) and other previous studies, Beijing, Liaoning, Jiangsu, and Guangdong are classified as the coastal region. The remaining provinces, Shanxi, Anhui, Henan, Hubei, Yunnan, and Gansu are classified as the inland region.

It would be more desirable if I could also divide the region-education-experience group by sex. However, due to the small sample size, supply and demand differences in sex are not

[9] I am deeply appreciative of Professor Fields, who suggested to me that I examine supply and demand differences between coastal and inland regions.

taken into account in this analysis. However, including region instead of sex seems more appropriate considering that labor market segmentation by province is much more significant than that by sex in urban China as seen in Table 1 and Table 2.

In this way, I have divided the entire sample into 30 region-education-experience skill groups and nine industries. There are two regions (coastal or inland), three education groups (*High edu* = college or above, and professional school, *Middle edu* = middle level professional, technical or vocational, and upper middle school, *Low edu* = lower middle school, and elementary school or below), and six experience groups (1 = 0-9, 2 = 10-15, 3 = 15-20, 4 = 20-25, 5 = 25-30, and 6 = 30+ years experience). Although all region-education-experience group combinations total 36 (2*3*6) groups, I have merged several experience groups into region-education groups in order to avoid zero observation in each cell *ij*. As a result, there are 30 skill groups. Classification of skill groups and industries is presented in Table 3 and Table 4, respectively.

When dividing observations in each skill group by nine industries, many cells contain a small number of observations. Although this can be a cause of error in the estimation procedure, a small number of skill groups and industries can also cause error. Nearly 30 skill groups are required in order to estimate each skill group's earnings change due to the changes in SDG, since the number of observations used in the regression equation (1) equals the number of skill groups. A greater number of industry groups enables a more precise estimate of the relative demand shift between industries. Thus, 30 skill groups and nine industries are used in this analysis.

4. Results

4.1 Estimation of $\Delta \ln W_{i,t}$, $SUP_{i,t}$, $DEM_{i,t}$, *and* $\Delta(\ln x_j)$

Table 5 displays the estimation result of $\Delta \ln W_{i,t}$ (competitive cell mean relative earnings change), $SUP_{i,t}$ (supply shift index), and $DEM_{i,t}$ (product demand shift index) for 30 skill groups from both periods, 1988 to 1995 and 1995 to 2002. (The classification of the 30 skill groups are presented in Table 3.) In order to make the interpretation of Table 5 easier, Table 6 aggregates the results of Table 5 by two regions, three education groups, two experience groups, and the education and experience groups by two regions. As shown in Table 6, from 1988 to 1995, the estimated $\Delta \ln W_{i,t}$ (see columns labeled dlnwi) is positive for the coastal region, the highly educated (college and above, and professional school) and the middle-level educated (middle level professional, technical or vocational, and upper middle school), and the less experienced (0-19 years experience). It is negative for the inland region, the low educated (lower middle school, and elementary school and below), and the more experienced. From 1995 to 2002, $\Delta \ln W_{i,t}$ is positive for the inland region, the highly educated, the middle-level educated, and the less experienced. As seen in Asuyama (2008), earnings inequality between coastal and inland regions declined from 1995 to 2002, and the movement of $\Delta \ln W_{i,t}$ by region reflects that trend.

With regard to $SUP_{i,t}$ and $DEM_{i,t}$, both the relative supply and product demand increased for the workers in the coastal region (or relative supply and product demand decreased for the workers in the inland region) in both periods. There is almost no change in the size of the relative product demand shift for the two regions in both periods. However, the relative labor supply increase in the coastal region (or the relative labor supply decrease in inland region) became greater from 1995 to 2002. The relative product demand increased for the low educated and the middle-level educated, while it decreased for the highly educated from 1988 to 1995. In contrast, from 1995 to 2002, the relative product demand increased for the highly educated and the middle-level educated, and decreased for the low educated. The supply of the highly educated increased substantially, while that of the low educated decreased greatly during both periods. During both periods, the relative product demand increased for the less experienced group. The relative supply of the less experienced (0-19 years experience) when compared to the more experienced (20+ years experience), increased from 1988 to 1995, while it decreased from 1995 to 2002. The relative supply and product demand shifts were both larger in the coastal region in the most educated and experienced groups.

As explained in step 4 in the previous section, in advance of estimating $DEM_{i,t}$, $\Delta(\ln x_j)$ (relative product demand shift for industry *j*) must be estimated. Table 7 reports the estimation results of $\Delta(\ln x_j)$ for both periods. For the period from 1988 to 1995, the relative product demand shift is positive and largest for industry 6 (real estate, public utilities, personal & consulting services, social services, and finance & insurance), followed by industry 5 (commerce & trade, restaurants & catering, materials supply, marketing, and warehousing), and industry 9 (government, Party organs, and social organizations). The coefficient for manufacturing (industry 2) is also positive but statistically insignificant. In contrast, the relative demand shifts for industries such as industry 1 (agriculture, mining and other), 3 (construction), 8 (education and scientific research), 7 (health, physical culture and social welfare), and 4 (transportation, communications, and post & telecommunications) are negative.

For the period from 1995 to 2002, the relative demand shift is positive and largest for industry 6 (real estate, public utilities, personal & consulting services, social services, and finance & insurance), followed by industry 1 (agriculture, mining and other), industry 4 (transportation, communications, and post & telecommunications), and industry 3 (construction). A negative relative demand shift is observed for industry 5 (commerce & trade, restaurants & catering, materials supply, marketing, and warehousing), industry 2 (manufacturing), and industry 9 (government, Party organs, and social organizations). The coefficients for industry 7 (health, physical culture and social welfare) and 8 (education and scientific research) are not statistically significant. In sum, a demand increase for some service industries and a demand decrease for manufacturing (only for the 1995-2002 period) are observed. As examined in the data description section of Asuyama (2008), the employment share of manufacturing declined dramatically from 41.1% to 25.2% between 1995 and 2002 in my CHIP sample. This is consistent with the statistics of total urban employment drawn from the China Labour Statistical Yearbook (CLSY). CLSY reports that the proportion of manufacturing in urban employment declined from 35.9% to 27.1% in the period 1995 to 2002. Although the relative demand increase for industry 1 (agriculture, mining, and other) seems unexpected, the employment share of those mixed industries increased in my CHIP sample due to the share increase in mining and other industries. However, in the CLSY statistics, the proportion of industry 1 declined slightly from 11.7% to 11.1%.

4.2 Estimated cell mean earnings change due to the changes in SDG

Table 8 presents the WLS regression results of $\Delta \ln W_{i,t}$ on $SUP_{i,t}$ and $DEM_{i,t}$. In Model 1, only $SUP_{i,t}$ and $DEM_{i,t}$ are included as explanatory variables. The pace of technological change $(\Delta \ln b_{i,t2} - \Delta \ln b_{i,t1})$ is assumed to be identical across all skill groups and $(1-1/\sigma)(\Delta \ln b_{i,t2} - \Delta \ln b_{i,t1})$ is treated as a constant term. The obtained coefficients are -0.019 for $SUP_{i,t}$ and 1.141 for $DEM_{i,t}$ with F-Statistics 2.4 (p-value: 0.11), although the estimated coefficient for $SUP_{i,t}$ is not statistically significant.

Next, in order to check whether the initial assumption of an identical technological growth across all skill groups is appropriate, dummies for the region, education, and experience groups were added. Only the region dummy was added in Model 2, and region, education, and experience dummies were all added in Model 3. The results of Model 2 and Model 3 clearly show that only the coefficient for the region dummy is statistically significant and the addition of a region dummy greatly increases the goodness of fit of the model (i.e. the region factor explains the largest part of the competitive earnings change). Adding only a region dummy does not change the coefficients for $SUP_{i,t}$ and $DEM_{i,t}$ significantly. In Model 2, the coefficients for $SUP_{i,t}$ and $DEM_{i,t}$ are -0.009 and 1.252, respectively. Again, the coefficient for $SUP_{i,t}$ is statistically insignificant.

The results from Model 1 and Model 2 suggest that: 1) supply shift across skill groups did not affect the earnings change in urban China at all, or if there were any effects their magnitude was very small, 2) in contrast, product demand shift did affect the earnings change in urban China from 1988 to 2002. Also, if we interpret our theoretical model literally, the result from Model 2 indicates that 1) earnings changes in skill groups were largely explained by general technological change, 2) the pace of technological change was not identical, but differed across skill groups (i.e. $A_i = A_0 + A_{1i}$), and 3) the pace of technological change was greater in the inland region (What "general technological change" really stands for and the validity of the theoretical model will be examined in the discussion section below).

4.3 Contribution of SDG to earnings inequality

Since the explanatory power and the overall statistical significance of Model 2 is much better than Model 1, and the fact of the declining earnings inequality between the coastal and inland regions from 1995 to 2002 is consistent with the results of Model 2, I have used Model 2 to analyze the contribution of the supply shift, product demand shift, and general technological change to earnings inequality.[10] Although the coefficients for $SUP_{i,t}$ are not statistically significant, by using the coefficients obtained from Model 2 in Table 8, and following step 5, I have estimated the competitive cell mean relative earnings change due to 1) the supply shift ($-(1/\sigma)SUP_{i,t}$), 2) the product demand-shift ($(1/\sigma)DEM_{i,t}$), and 3) the remaining factor, which represents general technological change ($(1-1/\sigma)\Delta \ln b_{i,t}$). The estimated results are presented in Table 9. First, it is clear that the competitive cell mean relative earnings change for all groups can be largely explained by the remaining factor, representing general technological change. Second, the competitive cell mean earnings change due to the remaining factor is greater for the higher educated and the less experienced in both periods. It is greater for the coastal region in the period 1988 to 1995, but greater for the inland region in the period 1995 to 2002. Third, since the coefficient for $SUP_{i,t}$ is very small, the magnitude of earnings change due to supply shift is almost always smaller than that due to product demand shift.

Next, I constructed four counterfactual earnings distributions, $f(\ln W)_{noS}$, $f(\ln W)_{noD}$, $f(\ln W)_{noG}$, and $f(\ln W)_{noSDG}$ by using the coefficients obtained from Model 2. Following step 6, the effects of 1) supply shift (S_effect), 2) product-demand shift

[10] However, since the size of the coefficients for SUPi and DEMi are almost the same in Model 1 and Model 2, using Model 1 does not significantly change the result of supply and product demand shift effects obtained.

(D_effect), 3) general technological change (G_effect), and 4) all three shifts (SDG_effect) on earnings inequality change were then calculated individually. Table 10 reports the effects of S_effect, D_effect, G_effect, and SDG_effect on the inequality of RPD-adjusted earnings. In Table 10, a positive sign indicates a disequalizing effect and a negative sign indicates an equalizing effect. Without a supply shift since 1988, the earnings distribution in 1995 would have been slightly less equal. This is also true for 2002. In other words, the supply shift contributed to reducing earnings inequality in both periods, 1988 to 1995 and 1995 to 2002, although the magnitude of supply shift was very small (-1.1 % for both periods, measured by the Gini coefficient). Product demand shift contributed greatly to the reduction of inequality in the period 1988 to 1995. It reduces the increase in the Gini coefficient by -18.7%. In contrast, from 1995 to 2002, a product demand shift contributed to an increase in inequality in almost all inequality measures (1.4% by the Gini coefficient), although its magnitude was small and almost offset by the supply shift effect. In both periods, the remaining factor, which theoretically represents general technological change, is the largest contributor to the earnings inequality increase. For example, the G_effect on the increase in inequality was 30.0% from 1988 to 1995 and 15.2% from 1995 to 2002 in terms of the changes in the Gini coefficient.

4.4 Decomposing inequality into SDG and other factors

Table 11 compares the five inequality decomposition results. Following step 7, the upper three results decompose the RPD-adjusted earnings into either an S_effect, D_effect, or G_effect, and other factors. The lower-left result decomposes the RPD-adjusted earnings into the SDG_effect and other factors. The lower-right result decomposes the RPD-adjusted earnings into only other factors without factoring out SDG effects (the same decomposition result as in Table 1, although Table 11 includes the residual contribution in the 100% total, while Table 1 does not). As expected, the factors whose contributions are mainly affected by introducing SDG effects are education, experience, and province. This is because the earnings change due to SDG effects was subtracted based on the region-education-experience group in order to remove the SDG effects. Table 11 can be read as follows: if the size of the contribution of education in the results of “Factoring out D_effect” is greater than that in the lower-right results of “Not factoring out SDG_effect,” it means that without the product demand shift effect, the contribution of education would have been larger, i.e. product demand shift contributed to reducing the earnings gap between education groups. On the contrary, if the contribution of education in the former results is smaller, it means that product demand shift contributed to increasing the earnings gap between education groups.

As seen in Table 11, the moderate rise in the educational earnings differentials from 1988 to 1995 is largely explained by the remaining factor, representing general technological change. Both supply and product demand shifts contributed to equalizing the earnings gap among education groups. In contrast, in the period from 1995 to 2002, the product demand shift contributed to the overall large increase in the educational earnings differentials. However, the general technological change remains the largest contributor to the rise in educational earnings differentials. Again, the supply shift worked as an equalizing force.

The rise in the inter-provincial earnings differentials from 1988 to 1995 is explained largely by the remaining factor and also by the product demand shift. The supply shift contributed to a reduction in the inter-provincial earnings gap. The fall in the inter-provincial earnings differentials from 1995 to 2002 is explained by the remaining factor and slightly by the supply shift. The product demand shift still contributed to an increase in the earnings gap between provinces, reflecting the continuous demand increase in the coastal region.

Concerning the earnings gap among experience groups, the supply shift, the product demand shift, and the remaining factor, all contributed to a reduction in the gap during both periods. Finally, as expected, the SDG effect as a whole contributed to an increase in the earnings differentials between education groups in both periods, and those between provinces from 1988 to 1995, and contributed to a decrease in the earnings differentials between provinces from 1995 to 2002 and between experience groups during both periods.

5. Discussion

In this section, I summarize and offer interpretations of the results. The estimation results obtained in the previous section indicate that the product demand shift across skill groups and the remaining factor, representing the general technological change, did affect the changes in earnings inequality in urban China in the period from 1988 to 2002. The product demand shift contributed to a substantial reduction in inequality from 1988 to 1995, and contributed to a slight widening of inequality from 1995 to 2002. The remaining factor greatly contributed to the rise in inequality during both periods. In contrast, the supply shift across skill groups contributed essentially nothing during both periods. If any supply shift effect exists at all, it contributed only slightly to a reduction in earnings inequality.

5.1 Supply shift and product demand shift

Education: In the period from 1988 to 1995, both supply and product demand shifts contributed to a reduction in educational earnings differentials, reflecting a relative demand decrease for the highly educated (= relative demand increase for the low educated) combined with a relative supply increase in the highly educated. On the other hand, from 1995 to 2002, the product demand shift contributed to an increase in the educational earnings gap, by increasing the relative demand for the highly educated and decreasing that for the low educated. The relative supply of the highly educated continuously increased and thus worked as an equalizing force.

In the US, many studies claim that the relative demand increase for skill-intensive domestic products due to "globalization," especially increased imports from developing countries, raised the relative demand for highly educated labor, and thus contributed to an increase in inequality (Ehrenberg & Smith, 2006; Katz & Autor, 1999; Johnson, 1997).[11] In the

[11] However, it should be noted that even in the US the contribution of product demand shift was considered rather small (Ehrenberg & Smith, 2006; Johnson, 1997). In fact, Bound and Johnson (1992) found that the effects of product demand shift on educational wage differentials in the US in the periods 1973 to 1979 and 1979 to 1988 were small and mixed (having effects in both directions).

case of urban China, we observed the opposite trend in the period 1988 to 1995 and a similar trend in the period 1995 to 2002. As Liu, Park, and Zhao (2007) suggest, the trend seen in the first period may be due to China's comparative advantage in low-cost and low-skilled labor, mainly in manufacturing. Consequently, China attracted foreign companies which wished to utilize the low-cost labor, and thus, the relative demand for low-educated workers may have increased. The opposite trend, the relative product demand for the highly educated increasing during the second period, can be interpreted as involving the shift from manufacturing to service industries. As shown in Table 7, the relative demand for manufacturing increased from 1988 to 1995 (although it is statistically insignificant), but decreased from 1995 to 2002. Instead, the relative demand for certain service industries, such as industry 6 (real estate, public utilities, personal & consulting services, social services, and finance & insurance) and industry 4 (transportation, communications, and post & telecommunications), which demands more highly skilled labor compared to manufacturing, increased. Additionally, the trend shift from 1988-1995 to 1995-2002 can be interpreted as an improved functioning of the labor market mechanism in urban China. As described in Asuyama (2008), labor mobility became more flexible in the late 1990s as the 1994 Labor Law was enforced and worker lay-offs increased. With the better functioning of the labor market, supply and demand shift is likely to have larger effects.

Experience: Both supply shift and product demand shift contributed to a reduction in earnings differentials between experience groups by reflecting the relative demand increase for the less experienced in both periods. The relative supply decrease in the less experienced also contributed to the reduction in inequality from 1995 to 2002. Although the relative supply of the less experienced increased in the period 1988 to 1995, its disequalizing effect was very small.

Region: Compared to the inland region, both the relative labor supply and product demand increased in the coastal region in both periods. A greater magnitude of product demand shift effect on earnings change than that of supply shift effect contributed to an increase in the earnings gap between coastal and inland regions in both periods. The fall in the earnings differentials between coastal and inland regions between 1995 and 2002 is explained by the remaining factor.

5.2 General technological change?

The largest contributor to the increase in inequality in urban China in both periods was the remaining factor, which theoretically represents general technological change. However, the interpretation of "general technological change" is a little problematic. If we stick to the theoretical model we have used, the remaining factor represents the technological change effect. The technological change in favor of the highly educated and the less experienced workers increases the relative demand for those workers, and thus contributed to the rise in earnings inequality. Although such an explanation is partially possible, it is difficult to accept that the remaining factor is entirely explained by this kind of biased technological change in urban China. In the US, where there is ample data and various empirical studies, the view that skill-biased technological change is considered the most important factor in increases in inequality is widely supported by many researchers.[12] However, for urban China, the interpretation that the remaining factor mainly represents some biased technological changes is not plausible. Along with rapid economic development and the introduction of foreign direct investment (FDI), it is highly likely that technological growth occurred in many industries in urban China. However, there is insufficient evidence to conclude that such technological change is biased towards the highly educated and the less experienced. If the technological change was neutral (i.e. technological change increases the productivity of all skill groups proportionally), it should not increase the relative demand for the highly educated, and thus not contribute to the

[12] For example, Bound and Johnson (1992) also considered alternative explanations for the remaining "general technological change" factor, such as an improvement in the unobserved labor quality of women, a decline in labor-market discrimination against women, a decline in the quality of precollege education, and the underestimation of the supply effect due to the exclusion of undocumented immigrants. However, Bound and Johnson were in favor of interpreting the remaining factor as skill-biased technological change, showing some evidence for this (e.g. an association between computer use and higher wages, and an association between increase in "high-tech" capital and an increase in labor demand for more skilled workers in the manufacturing sector).

rise in the educational earnings gap. It is also hard to justify the literal interpretation that the pace of technological change was slower in the coastal region than in the inland region in the period from 1995 to 2002.

If we depart from the assumption of our model, "general technological change" only represents everything that remained after removing supply and product demand shift effects. What factors might then explain such a large residual? First, as Liu, Park, and Zhao (2007) conclude, "the changes in technical changes could be caused by both the skill-biased technical changes and skill-biased institutional changes." As discussed in Asuyama (2008), due to the market-oriented institutional reforms, skills, represented by education and occupation (but not by experience), seem to have become more "accurately" evaluated in urban China. Such skill (high education)-biased institutional changes can enlarge the educational earnings differentials even without skill (high education)-biased technological changes.

Second, the magnitude of the supply shift effect is underestimated, since the sample largely excludes rural-urban migrant workers, and thus the supply of the lower educated is underestimated. Due to this bias, the magnitude of the remaining factor is likely to be overestimated, in particular in the period 1995 to 2002.[13] The reduction in the coastal-inland earnings inequality from 1995 to 2002, despite the relative demand increase for labor in the coastal region, can be partly explained by the exclusion of migrant workers, the inflow of whom was much larger in the coastal region. If we calculate the net migration to the four coastal provinces and six inland provinces by using the data in Fan (2005), who examined the 1990 and 2000 Chinese censuses, the net migration to the four coastal provinces increased from 1.9 million people in the period between 1985 and 1990 to 13.8 million in the period between 1995 and 2000. On the other hand, the net migration to the six inland provinces was negative; -0.3

[13] That is, between 1995 and 2002, inclusion of more migrant workers into the CHIP sample would increase the equalizing effect of supply shift on provinces, and reduce the equalizing effect of the remaining factor. It would also decrease the equalizing effect of supply shift on education and reduce the disequalizing effect of the remaining factor. Although the impact of including migrant workers may be smaller, including migrant workers for the period between 1988 and 1995 would *increase* the disequalizing effect of the remaining factor on province. In this case, exclusion of most of migrant workers causes the remaining factor to be underestimated concerning interregional inequality.

million during the former period and -6.0 million during the latter period. These figures cover both urban and rural areas and workers with urban *hukou* status. However, the magnitude of the rural migrant inflow was also larger in the coastal region. As Table 12 shows, the proportion of rural workers in urban staff and worker employment increased in three coastal provinces while it decreased in all six inland provinces in the period from 1995 to 2002.[14] The larger inflow of rural migrants into the coastal region may have suppressed the earnings of the low-skilled urban workers who had to compete with those migrants, and consequently caused the rise in mean earnings in the coastal region to be relatively moderate. In fact, earnings differentials between highly educated and less educated workers became significantly larger within the coastal region in the period from 1995 to 2002. Table 13 displays the estimated coefficients for education dummies obtained from the OLS regressions of RPD-adjusted log earnings in the two regions. In 1995, the least educated group (elementary and below) earned about 41% less than the most educated (college and above) in the coastal region, and 38% less in the inland region. However, in 2002, the gap increased greatly in the coastal region (-74%), while it remained almost the same (-39%) in the inland region.

Third, the product demand shift may also be downward biased, making the remaining factor upward biased. As Liu, Park, and Zhao (2007) note, the product demand shift effect is underestimated because the relatively broad classification of industries may treat some of the between-industry product demand shifts as within-industry shifts. The broad classification of education, experience, and region, in particular, may also make both product demand shift and supply shift downward biased, making the remaining factor upward biased.

Finally, an increase in the quality gap between different education levels may be one cause for the large remaining factor. For example, if the quality of college education improved

[14] In China, "staff and workers" are defined as a certain category of workers. They include workers who receive payment from units under state ownership, collective ownership, joint ownership, shareholding ownership, foreign ownership, and ownership by entrepreneurs from Hong Kong, Macao, and Taiwan. They do not include workers such as those employed in township enterprises and private enterprises, self-employed workers, retirees, and re-employed retirees, teachers in schools run by the local people, and foreigners and workers from Hong Kong, Macao and Taiwan (China Statistical Yearbook (CSY). For more detail, refer to CSY).

relative to other levels of education, it might result in rising returns to college education. However, further research is needed to confirm this explanation.

5.3 Comparison with the existing literature

The above results are partly consistent with the findings of Liu, Park, and Zhao (2007), who applied the method of Bound and Johnson (1992) directly to China's Urban Household Survey data from 1990 to 2001 and decomposed the wage differentials between education groups in urban China. They obtained the coefficient 0.132 for the net demand ($DEM_{i,t} - SUP_{i,t}$), although it was not statistically significant at the 10% level (standard error = 0.12). Their decomposition results show that general technological change accounts for most of the increase in wage differentials between education groups, while both changes in relative labor supply and product demand contributed to an equalization in wage differentials between education groups from both periods, 1991 to 1996 and 1996 to 2001. A similar trend for 1988 to 1995 has been found here. However, in contrast to the results of Liu et al. (2007), my results indicated that the product demand shift contributed to an increase in educational earnings differentials from 1995 to 2002. The use of region instead of sex to construct the skill groups in my model seems to have generated the difference. In fact, when I used sex-education-experience groups, I obtained a result similar to that of Liu et al. (2007). As mentioned earlier, using region instead of sex to construct skill groups seems more appropriate in urban China, where the labor market segmentation by province is salient. Thus, by taking into account the supply and demand differences between coastal and inland regions, this paper has been able to uncover a new trend occurring in urban China, namely that product demand shift contributed to a widening of educational earnings differentials in the late 1990s by increasing the relative demand for the highly educated. At the same time, this paper also contributes to the existing literature by examining the supply and demand shift effect between coastal and inland regions.

6. Conclusions

6.1 Summary of the findings

This paper has examined the degree to which supply and demand shift across skill groups contributed to an earnings inequality increase in urban China from 1988 to 2002. The same individual samples examined in Asuyama (2008) were used, being taken originally from urban Chinese resident data for 1988, 1995, and 2002 drawn from the Chinese Household Income Project (CHIP). By following the methods of DiNardo, Fortin, and Lemieux (1996) and Bound and Johnson (1992), 30 skill groups defined by region-education-experience were constructed and used to estimate the contributions of supply shift, product demand shift, and remaining factor including general technological change, to earnings inequality increase.

Product demand shift contributed to an equalization in earnings distribution in urban China from 1988 to 1995 by increasing the relative product demand for the low educated. However, in the period from 1995 to 2002, product demand shift contributed to a widening of inequality by increasing the relative product demand for the highly educated. This may have been due to the shift from manufacturing to service industries as well as the improved functioning of labor market mechanisms. Relative product demand was continuously higher for workers in the coastal region and contributed to a rise in interregional inequality.

Supply shift across skill groups contributed essentially nothing or only slightly contributed to a reduction in inequality during both periods, 1988 to 1995 and 1995 to 2002.

Remaining factors, which were the largest contributor to the increase in inequality, may contain both skill-biased technological changes and skill-biased institutional changes. They may also include an unobserved supply shift effect due to increasing numbers of migrant workers. A larger inflow of rural migrants into the coastal region may have suppressed the earnings of low-skilled urban workers who had to compete with those migrants, and consequently caused the rise in the mean earnings of the coastal region to be relatively moderate. Since migrant workers with rural *hukou* status are largely omitted from the CHIP sample, the supply effect might be underestimated and thus the remaining factor might be overestimated. A larger inflow of migrant workers into the costal region may be one of the causes for the decline in the inter-provincial earnings inequality in the period 1995 to 2002.

6.2 Limitations of my analysis

Finally, the limitations of this analysis should also be kept in mind. First, the size of my CHIP sample may not be sufficient to obtain a firm conclusion. For example, in Bound and Johnson (1992), the sample size was 66,808 for 1973-1974, 145,744 for 1979, and 149,011 for 1988; 32 skill groups and 17 industries were used. As described previously, a small number of observations in each cell, the relatively broad classification of region, education, and industries, and the exclusion of the factor of sex, might have caused errors in my estimation. As mentioned above, exclusion of most of migrant workers may also have resulted in an underestimation of the effect of the supply shift and made it statistically insignificant.

Second, the assumptions of the theoretical model may still not be appropriate for urban China. For example, since my classification of region and education group is relatively broad, the assumption of homogeneous labor within each skill group may not be valid. In addition, since the competitive labor market was in fact under construction and gradually evolving in urban China during the period 1988 to 2002, the application of a similar model to that used for the US labor market to urban China while assuming that the elasticity is constant over time and of equal magnitude across skill groups, may not be appropriate. It is essential to build a more appropriate model for urban China, where the labor market is imperfect and segmented.

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Table 1. Decomposition of inequality levels and increases

(Unit: % except inequality indices)

	1988	1995	2002	Gini		log-variance	
				88-95	95-02	88-95	95-02
sex	5.45	4.74	4.91	-5.20	6.22	3.49	5.18
min	-0.02	0.22	0.02	3.59	-1.45	0.65	-0.28
cp	4.22	3.57	2.09	-5.54	-8.88	2.42	-0.18
exp	64.80	35.54	10.06	-374.78	-178.87	-16.13	-29.01
edu	5.13	8.57	16.91	56.76	78.79	14.64	29.71
occ	5.55	7.65	12.34	37.08	47.11	11.36	19.53
own	6.71	7.91	6.08	24.70	-7.42	10.02	3.29
ind	-0.77	3.67	7.86	66.02	38.87	11.53	14.27
emp	3.61	1.69	27.55	-25.24	219.31	-1.70	67.21
prov	5.32	26.44	12.17	322.61	-93.68	63.75	-9.72
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Total explained	39.74	35.61	34.04	14.49	25.67	30.09	31.89
Gini	**0.233**	**0.278**	**0.330**	**0.046**	**0.052**	**-**	**-**
log-variance	**0.195**	**0.341**	**0.589**	**-**	**-**	**0.146**	**0.248**

Notes: Figures indicate the percentage contribution of each factor to the inequality levels and their changes.
In the inequality level decomposition, the magnitude of contribution of each factor,
does not depend on the inequality index used.
The contribution of each factor is calculated by setting "Total explained" as 100%,
where Total explained = R-squared =100% - residual contribution.
The dependent variable is RPD-adjusted log earnings.
For the inequality decomposition method, see Asuyama (2008) or step 7 in this paper.
Source: Table 5 and 6 in Asuyama (2008)

Table 2. Decomposition of inequality increase into price and quantity effects (log-variance)

(Unit: % except index)

	88-95	of which		within each factor		95-02	of which		within each factor	
		Price effect	Quantity effect	Price effect	Quantity effect		Price effect	Quantity effect	Price effect	Quantity effect
	(Sj)	(P1)	(Q1)	(P2)	(Q2)	(Sj)	(P1)	(Q1)	(P2)	(Q2)
sex	3.49	2.77	0.71	79.58	20.42	5.18	5.84	-0.65	112.63	-12.63
min	0.65	0.61	0.04	93.90	6.10	-0.28	-0.33	0.05	116.57	-16.57
cp	2.42	2.10	0.32	86.83	13.17	-0.18	-0.08	-0.10	44.81	55.19
exp	-16.13	-17.51	1.38	108.55	-8.55	-29.01	-25.17	-3.84	86.75	13.25
edu	14.64	4.21	10.42	28.79	71.21	29.71	31.97	-2.26	107.60	-7.60
occ	11.36	9.47	1.88	83.40	16.60	19.53	21.10	-1.57	108.06	-8.06
own	10.02	10.74	-0.72	107.14	-7.14	3.29	3.46	-0.17	105.05	-5.05
ind	11.53	9.90	1.62	85.91	14.09	14.27	11.36	2.91	79.64	20.36
emp	-1.70	-6.07	4.37	356.27	-256.27	67.21	55.70	11.51	82.87	17.13
prov	63.75	60.67	3.08	95.17	4.83	-9.72	-9.48	-0.24	97.55	2.45
Total	**100.00**	**76.89**	**23.11**	**76.89**	**23.11**	**100.00**	**94.37**	**5.63**	**94.37**	**5.63**
Total explained	30.09					31.89				
Index	**0.146**					**0.248**				

Notes: The contribution of each factor (Sj) is calculated by setting "Total explained" as 100%,
where Total explained = 100% - residual contribution.
The sum of (P1) and (Q1) for each factor is equal to (Sj).
(P2) and (Q2) are calculated by setting the contribution of each factor (Sj) = 100%
The dependent variable is RPD-adjusted log earnings.
Source: Table 7 in Asuyama (2008)

Table 3. Classification of 30 skill groups

I	Region	Education	Experience
1	Inland	High	1
2	Inland	High	2
3	Inland	High	3
4	Inland	High	4
5	Inland	High	**5&6**
6	Inland	Middle	1
7	Inland	Middle	2
8	Inland	Middle	3
9	Inland	Middle	4
10	Inland	Middle	5
11	Inland	Middle	6
12	Inland	Low	1
13	Inland	Low	2
14	Inland	Low	3
15	Inland	Low	4
16	Inland	Low	5
17	Inland	Low	6
18	Coastal	High	1
19	Coastal	High	**2&3**
20	Coastal	High	**4&5**
21	Coastal	High	6
22	Coastal	Middle	1
23	Coastal	Middle	2
24	Coastal	Middle	3
25	Coastal	Middle	4
26	Coastal	Middle	5
27	Coastal	Middle	6
28	Coastal	Low	**1&2&3**
29	Coastal	Low	**4&5**
30	Coastal	Low	6

Notes: Region: Inland=inland region (Shanxi, Anhui, Henan, Hubei, Yunnan, and Gansu).
Coastal=coastal region (Beijing, Liaoning, Jiangsu, and Guandong)
Education: High=college or above, and professional school,
Middle=middle level professional, technical or vocational, and upper middle,
Low=lower middle, and elementary or below
Experience: 1=0-9, 2=10-15, 3=15-20, 4=20-25, 5=25-30, 6=30+ years experience
Two or three experience groups are merged into skill groups 5, 19, 20, 28, and 29.

Table 4. Classification of nine industries

J	
1	agriculture, mining, geological survey & prospecting, and other
2	manufacturing
3	construction
4	transportation, communications, and post & telecommunications
5	commerce & trade, restaurants & catering, materials supply, marketing, and warehousing
6	real estate, public utilities, personal & consulting services, social services, and finance & insurance
7	health, physical culture and social welfare
8	education, culture, arts, and scientific research & technical service
9	government and Party organs, and social organizations

Table 5. Estimation results of $\Delta \ln W_{i,t}$, $SUP_{i,t}$, and $DEM_{i,t}$ by 30 skill groups

Skill group	1988-1995			1995-2002			classificaton of skill group		
	dlnwi	**SUPi**	**DEMi**	**dlnwi**	**SUPi**	**DEMi**	**Region**	**Edu**	**Exp**
1	-0.149	0.336	-0.023	0.163	0.231	0.039	In	H	1
2	-0.060	0.790	-0.034	0.108	0.481	0.002	In	H	2
3	-0.065	0.391	-0.040	0.118	0.867	0.022	In	H	3
4	-0.114	0.381	-0.114	0.082	0.853	-0.003	In	H	4
5	-0.089	0.703	-0.106	0.117	0.182	-0.020	In	H	5&6
6	-0.077	-0.174	-0.001	0.088	-0.523	0.022	In	M	1
7	-0.084	0.125	0.013	0.043	-0.549	-0.012	In	M	2
8	-0.057	0.572	-0.005	0.031	-0.411	0.000	In	M	3
9	-0.078	0.476	-0.012	0.071	0.358	0.028	In	M	4
10	-0.053	0.303	-0.052	-0.010	0.250	-0.033	In	M	5
11	-0.045	-0.045	-0.033	-0.105	-0.063	-0.016	In	M	6
12	-0.057	-0.331	0.005	0.058	-0.732	0.041	In	L	1
13	-0.020	0.136	-0.018	-0.100	-0.423	-0.046	In	L	2
14	-0.069	-0.342	0.010	-0.066	-0.336	-0.056	In	L	3
15	-0.071	-0.540	0.018	-0.210	-0.436	-0.054	In	L	4
16	-0.111	-0.074	0.014	-0.057	-0.862	-0.057	In	L	5
17	-0.094	-1.116	-0.004	-0.175	0.077	0.002	In	L	6
18	0.174	0.281	0.003	0.135	0.539	0.035	Co	H	1
19	0.176	0.442	-0.029	0.167	0.414	-0.003	Co	H	2&3
20	0.205	0.913	-0.075	0.136	-0.140	0.026	Co	H	4&5
21	0.153	1.018	-0.138	0.076	0.500	0.041	Co	H	6
22	0.199	-0.191	0.043	0.152	-0.202	0.068	Co	M	1
23	0.236	-0.440	0.031	0.044	-0.040	0.004	Co	M	2
24	0.130	0.447	0.013	-0.152	-0.329	-0.012	Co	M	3
25	0.182	0.318	-0.003	-0.033	0.502	-0.004	Co	M	4
26	0.122	0.516	-0.022	-0.057	0.266	0.006	Co	M	5
27	0.121	0.216	-0.006	-0.066	0.615	-0.011	Co	M	6
28	0.106	-0.279	0.032	-0.149	-0.568	0.010	Co	L	1&2&3
29	0.055	0.000	0.026	-0.104	-0.639	0.004	Co	L	4&5
30	-0.018	-0.832	0.019	-0.071	0.591	-0.008	Co	L	6

Notes: dlnwi ($\Delta \ln W_{i,t}$): competitive cell mean relative earnings change.
SUPi: supply shift index. DEMi: product demand shift index.
Classification of skill groups are as in Table 3.

Table 6. Estimation results of $\Delta \ln W_{i,t}$, $SUP_{i,t}$, and $DEM_{i,t}$ by aggregated groups

	1988-1995			1995-2002		
	dlnwi	**SUPi**	**DEMi**	**dlnwi**	**SUPi**	**DEMi**
Coastal	0.115	0.038	0.013	-0.013	0.053	0.012
Inland	-0.078	-0.027	-0.009	0.010	-0.040	-0.009
High edu	0.018	0.592	-0.057	0.126	0.387	0.013
Coastal	0.182	0.661	-0.049	0.132	0.273	0.023
Inland	-0.100	0.540	-0.063	0.121	0.470	0.005
Middle edu	0.031	0.145	0.001	0.014	-0.017	0.005
Coastal	0.178	0.094	0.018	-0.013	0.159	0.012
Inland	-0.068	0.178	-0.010	0.031	-0.144	0.001
Low edu	-0.027	-0.387	0.014	-0.105	-0.365	-0.015
Coastal	0.052	-0.281	0.026	-0.114	-0.285	0.004
Inland	-0.079	-0.467	0.006	-0.097	-0.435	-0.031
exp 0-19	0.025	0.038	0.009	0.034	-0.113	0.009
Coastal	0.161	-0.057	0.025	0.004	-0.067	0.018
Inland	-0.072	0.101	-0.003	0.053	-0.142	0.003
exp 20+	-0.022	-0.035	-0.008	-0.032	0.096	-0.008
Coastal	0.072	0.119	0.002	-0.027	0.136	0.008
Inland	-0.083	-0.149	-0.014	-0.037	0.061	-0.022

Notes: dlnwi is the weighted average dlnwi of each group (weight = number of individuals in each group in 1988 for 1988-1995 change and in 1995 for 1995-2002 change).
SUPi and DEMi are computed following step 3 and 4.
For the classification of region and education, see Table 3.
exp 0-19 and exp 20+ indicate a groups with 0-19 and 20+ years experience, respectively.

Table 7. Results of Estimation of $\Delta(\ln x_j)$

dlnxj	**1988-1995**			**1995-2002**			Industry
	Coef.	t		Coef.	t		
dlnx1	-0.401	-4.470	***	0.715	7.330	***	1: agri, min, other
dlnx2	0.049	1.140		-0.211	-4.410	***	2: manu
dlnx3	-0.373	-4.120	***	0.394	4.040	***	3: const
dlnx4	-0.200	-2.240	**	0.607	6.240	***	4: trans, post, tele
dlnx5	0.202	2.350	**	-0.212	-2.290	**	5: trade, restaurant
dlnx6	0.469	5.180	***	1.128	11.620	***	6: RE, PU, P&S serv, finance
dlnx7	-0.237	-2.620	***	0.083	0.850		7: health, social
dlnx8	-0.259	-3.120	***	-0.002	-0.020		8: edu, SR
dlnx9	0.195	2.220	**	-0.160	-1.770	*	9: govt
N	270			270			
F value	11.66			31.73			

Notes: In order to obtain the result, a constraint that the weighted average of relative demand shift (dlnxj) is equal to zero is imposed. (The weight is the proportion of total employment in each industry in total employment in the base period.)
The dependent variable is $\Delta(\ln \phi_{ij})$.
For the estimation procedure, see step 4. For the industry classification, see Table 4.
***denotes statistical significance at 1%, ** at 5%, and * at 10% level.

Table 8. WLS regression result of $\Delta \ln W_{i,t}$ on $SUP_{i,t}$ and $DEM_{i,t}$

	Model 1		Model 2		Model 3	
	Coef.	t	Coef.	t	Coef.	t
SUPi	-0.019	-0.38	-0.009	-0.32	-0.001	-0.02
DEMi	1.141	2.12 **	1.252	4.02 ***	0.612	1.20
Coast	-	-	-0.236	-7.39 ***	-0.231	-7.58 ***
Middle edu	-	-	-	-	-0.080	-1.56
Low edu	-	-	-	-	-0.115	-1.67
exp 20+	-	-	-	-	0.039	1.21
constant	-0.027	-0.91	0.073	3.31 ***	0.134	2.36 **
N	30		30		30	
F value	2.38		22.93		13.71	
R-squared	0.150		0.726		0.781	

Notes: The weight is the square root of the proportion of each skill group in 1995.
The dependent variable is dlnwi in second differences.
SUPi: supply shift index in second differences.
DEMi: product demand shift index in second differences.
Coast is the dummy for coastal region (the inland region is omitted).
Middle edu and Low edu are the education group dummies (High edu is omitted).
exp 20+ is the experience group dummy (exp 0-19 is omitted.)
For the classification of region, education, and experience groups, see Table 3.
For the estimation procedure, see step 5.
***denotes statistical significance at 1%, ** at 5%, and * at 10% level.

Table 9. Estimated competitive cell mean relative earnings change due to SDG by aggregated groups

	1988-1995				1995-2002			
	dlnwi	**S**	**D**	**G**	**dlnwi**	**S**	**D**	**G**
Coastal	0.115	0.001	0.016	0.108	-0.013	0.001	0.015	-0.029
Inland	-0.078	0.002	-0.011	-0.081	0.010	0.001	-0.011	0.019
High edu	0.018	-0.005	-0.071	0.118	0.126	-0.003	0.016	0.097
Coastal	0.182	-0.006	-0.061	0.262	0.132	-0.002	0.029	0.104
Inland	-0.100	-0.005	-0.079	0.014	0.121	-0.004	0.006	0.092
Middle edu	0.031	-0.001	0.001	0.033	0.014	0.001	0.006	0.008
Coastal	0.178	0.000	0.022	0.156	-0.013	-0.001	0.016	-0.019
Inland	-0.068	-0.001	-0.013	-0.050	0.031	0.002	0.001	0.025
Low edu	-0.027	0.004	0.018	-0.063	-0.105	0.004	-0.019	-0.080
Coastal	0.052	0.003	0.033	0.032	-0.114	0.004	0.005	-0.131
Inland	-0.079	0.005	0.007	-0.127	-0.097	0.005	-0.039	-0.039
exp 0-19	0.025	0.000	0.011	0.024	0.034	0.002	0.011	0.008
Coastal	0.161	0.001	0.032	0.130	0.004	0.001	0.022	-0.024
Inland	-0.072	0.000	-0.004	-0.051	0.053	0.002	0.004	0.028
exp 20+	-0.022	0.002	-0.010	-0.030	-0.032	0.000	-0.010	-0.010
Coastal	0.072	0.000	0.002	0.087	-0.027	0.000	0.010	-0.033
Inland	-0.083	0.003	-0.017	-0.106	-0.037	0.000	-0.027	0.009

Note: All figures are the weighted average of each group (weight = number of individuals in each group in 1988 for 1988-1995 change and in 1995 for 1995-2002 change).
dlnwi: competitive relative earnings change, S: dlnwi due to supply shift,
D: dlnwi due to product demand shift, and G: dlnwi due to general technological change.
Coefficients from Model 2 in Table 8 are used to estimate S, D, and G.
For the estimation procedure, see step 5.
Classification of region, education, and experience group is as in Table 3.

Table 10. Contribution of SDG to the inequality of RPD-adjusted earnings

(Unit: %)

	1995				1988-1995			
	S_effect	D_effect	G_effect	SDG_ effect	S_effect	D_effect	G_effect	SDG_ effect
Gini	-0.18	-3.05	4.91	2.75	-1.08	-18.65	30.04	16.80
Theil entropy	-0.35	-5.58	9.97	6.43	-1.58	-25.33	45.23	29.15
90/10	-0.34	-5.59	4.55	1.04	-1.39	-23.13	18.83	4.31
50/10	0.00	-2.31	1.94	-0.56	0.02	-15.48	13.01	-3.76
90/50	-0.34	-3.20	2.66	1.59	-3.13	-29.50	24.48	14.66
75/25	-0.16	-3.24	3.04	0.69	-1.25	-25.22	23.65	5.34
95/5	-0.02	-4.16	8.20	3.73	-0.05	-12.10	23.82	10.85
log-variance	-0.35	-5.07	7.18	2.88	-0.81	-11.85	16.78	6.74
	2002				1995-2002			
	S_effect	D_effect	G_effect	SDG_ effect	S_effect	D_effect	G_effect	SDG_ effect
Gini	-0.17	0.22	2.39	2.33	-1.09	1.40	15.15	14.76
Theil entropy	-0.32	0.59	4.75	4.76	-1.12	2.06	16.66	16.69
90/10	-0.53	0.70	5.34	4.93	-2.12	2.80	21.18	19.58
50/10	-0.27	0.34	3.24	2.37	-1.76	2.24	21.26	15.57
90/50	-0.26	0.36	2.17	2.62	-2.26	3.11	18.46	22.34
75/25	-0.55	-1.25	2.59	2.17	-3.32	-7.52	15.58	13.04
95/5	0.06	-0.33	4.33	4.01	0.19	-1.00	12.91	11.97
log-variance	-0.31	0.07	3.83	3.46	-0.75	0.17	9.09	8.22

Notes: Contribution of S (Supply shift), D (Product Demand shift), G (general technological change), and SDG (all three effects) to the inequality of RPD-adjusted earnings are calculated following step 6 of the individual decomposition.
The sum of the terms S_, D_, and G_effect does not equal SDG_effect due to the nature of individual decomposition.
This calculation is based on the coefficients obtained from Model 2 in Table 8.

Table 11. Inequality (Gini coefficient) decomposition of RPD-adjusted earnings into SDG effects and other factors (compared with the decomposition of RPD-adjusted earnings into only other factors)

(Unit: %)

	Factoring out S_effect				Factoring out D_effect				Factoring out G_effect			
	1995	2002	88-95	95-02	1995	2002	88-95	95-02	1995	2002	88-95	95-02
sex	1.68	1.68	-0.77	1.62	1.74	1.68	-0.42	1.67	1.65	1.69	-0.99	1.72
min	0.08	0.01	0.52	-0.37	0.08	0.01	0.53	-0.37	0.04	0.01	0.29	-0.39
cp	1.28	0.71	-0.76	-2.29	1.47	0.69	0.42	-2.42	1.09	0.62	-1.89	-2.86
exp	**12.74**	**3.47**	**-53.83**	**-45.60**	**14.79**	**4.23**	**-41.30**	**-40.82**	**13.30**	**3.65**	**-50.40**	**-44.49**
edu	**3.25**	**5.92**	**9.43**	**21.23**	**5.64**	**5.07**	**24.08**	**15.84**	**0.54**	**2.40**	**-7.10**	**-1.06**
occ	2.74	4.22	5.50	12.20	3.05	4.15	7.39	11.74	2.27	3.82	2.61	9.66
own	2.82	2.08	3.63	-1.87	2.87	2.04	3.90	-2.12	2.60	1.88	2.28	-3.13
ind	1.31	2.68	9.61	10.03	1.39	2.68	10.07	10.03	1.24	2.46	9.18	8.62
emp	0.60	9.39	-3.65	56.37	0.59	9.46	-3.71	56.78	0.67	9.19	-3.26	55.07
prov	**9.42**	**4.15**	**46.78**	**-24.00**	**8.48**	**3.88**	**41.03**	**-25.71**	**5.11**	**5.00**	**20.41**	**-18.60**
residual	64.25	65.86	84.64	73.76	62.94	65.90	76.66	73.97	66.57	66.90	98.84	80.31
S_effect	**-0.18**	**-0.17**	**-1.08**	**-1.09**	-	-	-	-	-	-	-	-
D_effect	-	-	-	-	**-3.05**	**0.22**	**-18.65**	**1.40**	-	-	-	-
G_effect	-	-	-	-	-	-	-	-	**4.91**	**2.39**	**30.04**	**15.15**
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

	Factoring out SDG_effect				Not factoring out SDG_effect			
	1995	2002	88-95	95-02	1995	2002	88-95	95-02
sex	1.71	1.71	-0.65	1.81	1.69	1.67	-0.75	1.60
min	0.05	0.01	0.32	-0.38	0.08	0.01	0.52	-0.37
cp	1.29	0.60	-0.70	-2.99	1.27	0.71	-0.80	-2.28
exp	**15.56**	**4.53**	**-36.57**	**-38.89**	**12.66**	**3.42**	**-54.32**	**-45.91**
edu	**1.91**	**2.08**	**1.25**	**-3.09**	**3.05**	**5.76**	**8.23**	**20.22**
occ	2.66	1.85	2.65	-3.32	2.72	4.20	5.37	12.09
own	2.63	3.78	4.81	9.40	2.82	2.07	3.58	-1.90
ind	1.34	2.48	9.74	8.73	1.31	2.67	9.57	9.98
emp	0.66	9.28	-3.31	55.64	0.60	9.38	-3.66	56.29
prov	**4.84**	**4.67**	**18.74**	**-20.67**	**9.42**	**4.14**	**46.76**	**-24.04**
residual	64.62	66.69	86.91	79.01	64.39	65.96	85.51	74.33
SDG_effec	**2.75**	**2.33**	**16.80**	**14.76**	-	-	-	-
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Notes: Total (=100%) is based on the Gini coefficient calculated based on PRD-adjusted earnings.
For the decomposition method, see step 7.

Table 12. Proportion of rural employment in urban work units (staff and workers)

(Unit: %)

		proportion			proportional change	
		1991	1995	2002	91-95	95-02
Coastal	Beijing	16.0	13.7	17.3	-2.3	3.6
	Liaoning	3.2	4.0	5.7	0.8	1.7
	Jiangsu	13.3	12.6	7.9	-0.7	-4.7
	Guangdong	11.2	18.6	19.7	7.4	1.1
Inland	Shanxi	16.0	11.4	7.8	-4.6	-3.6
	Anhui	6.4	9.3	7.2	2.9	-2.1
	Henan	9.5	10.1	7.6	0.6	-2.5
	Hubei	5.0	5.5	5.3	0.5	-0.2
	Yunnan	10.5	12.0	8.2	1.5	-3.8
	Gansu	5.3	9.1	5.5	3.8	-3.6

Source: China Labour Statistical Yearbook 1992, 1996, and 2003

Table 13. Estimated coefficients for education dummies obtained from earnings regressions for inland and coastal regions (Base category = edu1)

		1988		1995		2002	
		coef.	t	coef.	t	coef.	t
Coastal	edu2	-0.02	-0.80	-0.04	-1.24	-0.20	-5.22 ***
	edu3	-0.14	-7.67 ***	-0.15	-4.95 ***	-0.38	-9.46 ***
	edu4	-0.22	-10.71 ***	-0.25	-7.18 ***	-0.55	-11.55 ***
	edu5	-0.27	-9.93 ***	-0.41	-7.83 ***	-0.74	-7.35 ***
	N	6922		3989		3583	
	R-squared	0.340		0.312		0.338	
Inland	edu2	-0.03	-1.70 *	-0.13	-5.85 ***	-0.09	-2.51 **
	edu3	-0.17	-12.57 ***	-0.17	-8.18 ***	-0.22	-5.69 ***
	edu4	-0.25	-16.51 ***	-0.22	-8.73 ***	-0.38	-8.31 ***
	edu5	-0.34	-17.46 ***	-0.38	-8.81 ***	-0.39	-5.84 ***
	N	10163		5488		4494	
	R-squared	0.446		0.346		0.347	

Notes: The dependent variable is RPD-adjusted log earnings in the inland region and coastal region, respectively.
edu1(omitted): college or above, edu2: professional school, edu3: middle level professional, technical or vocational school, and upper middle school, edu4: lower middle school, edu5: elementary school and below. The explanatory variables, other than education dummies, are dummies for sex, minority status, CP membership, occupation, ownership, industry, employment status, and provinces.
Statistical significance is based on robust standard errors corrected for heteroscedasticity.
***denotes statistical significance at 1%, ** at 5%, and * at 10% level.