Comments are welcome.

Explaining Rising Return to Education in Urban China in the 1990s *

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Abstract

Using annual urban household survey data from 6 provinces in different regions of China, we analyze reasons behind the rise in education premium in urban China during the 1990s. Following Bound and Johnson (1992), we decompose the increase in education premium into four sources: changes in industrial wage rents, shifts in supply across educational levels, shifts in product demand across industries, and changes in relative technical efficiency. Our basic findings are: the increase in general technical efficiency and industrial wage rents are the major forces that drive up the relative wage of more-educated to less educated workers; shift in labor supply helps to negate the enlarging wage differentials between college and senior educated labors, but to increase the wage differential between senior and junior high school educated groups in the late 1990s; and the change in labor demand due to the shift in product demand also reduces educational wage differential but is relatively unimportant.

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I. Introduction

Wage inequality in urban China expanded rapidly in the 1990s due partly to increasing returns to education (Park et al., 2004). Based on repeated cross-sectional data between 1988 and 2001 drawn from urban household surveys in 6 provinces, Zhang et al. (2005) find that returns to education increased from only 4.0 percent in 1988 to 10.2 percent in 2001. Most of the rises in the returns to education occurred after 1992 and reflected an increase in the wage premium for higher education. The higher returns to education are observed within groups defined by sex, work experience, region, and ownership, and robust to the inclusion of different control variables.

Rising wage differentials by educational attainment has been observed around the world. The literature from developed countries has suggested a few alternative explanations: rising demand for skilled workers due to international trade in the product market, rising demand for skilled workers due to skill-biased technical progress, and institutional changes reducing the protection of less skilled workers (Katz and Murphy 1992; Healwege 1992; Bound and Johnson 1992; Juhn et al. 1993, among many others). The same forces are likely to exist in China as well. Liberalization in wage-setting in state-owned enterprises (SOEs) and the growth of non-SOEs have toppled the centralized wage-setting scheme that compressed the wage structure in the central planning era, resulting in higher rewards to human capital. By reentering the world market, China may have experienced changes in the demand for skills. Technological advances have also been substantial. It is, however, unclear whether these forces have the same directions of effects as in developed countries. Take international trade, for example, while it reduces demand for domestically-produced manufacturing goods in the United States which employ low-skilled workers, as a major trading partner with the U.S., China is expected to experience an increase in demand for products that are produced by low-skilled workers. However, this may not happen if China uses difference technologies than the U.S. For example, while being produced by low-skilled workers in the U.S., a same product may be produced by relatively high skilled workers in China.

In this paper, we evaluate the effects of institutional changes, technological change, the change in labor demand due to shifts in product demand and relative supply of skilled labor on rising skill premiums. We focus on the wage differential between workers with college education and above, senior high school education and junior high school education and below. Methodologically, we follow the basic analytical framework in Bound and Johnson (1992).

The remainder of the paper is organized as follows. Section II describes the data and the trends in wage differential across educational groups during the 1990s. Section III presents the analytical framework for explaining the changes in returns to education. Section IV reports empirical results. Section V summarizes the results.

II. Data and Rising Returns to Education

We use China's Urban Household Surveys (UHS) collected by the National Bureau of Statistics from 1989 to 2001 from six provinces: Beijing, Guangdong, Liaoning, Shaanxi, Sichuan and Zhejiang. These six provinces are roughly representative of China's different regions. Beijing is in North-Central China, Guangdong and Zhejiang are coastal provinces, Liaoning is in the Northeast, Shaanxi is in the Northwest, and Sichuan is in the Southwest. Table 1 reports sample sizes for each year after excluding people younger than 16, older than 60, students and the disabled.

Table 1. Sample Size, Urban Household Survey, Six Provinces, 1988-2001

To calculate wage differentials by educational levels, we first note that because the UHS data enumerates annual wages with no information on working hours, our wage is measured as annual wage. The total wage includes base wages, bonuses and subsidies and excludes capital gains and transfer income. To reduce bias from caused by variations in working hours, when computing wages by educational levels we confine our sample to full-time employees aged from 16 to 60, excluding individuals who are self-employed and re-employed retired workers. The size of the resultant full-time wage worker sample is about 6,000-7,000 individuals in each year (table 1).

Throughout the paper we focus on three data points: 1990, 1995 and 2000. The year 1990 and 2000 correspond to two censuses from where we draw additional information for the analysis. The mid-year 1995 was roughly the end of the first spur in rapidly rising returns to education (Park et al. 2004). At each data point we include neighboring 2 years to increase sample size and to smooth out short-run fluctuations. We classify education levels into three: "college" are college educated which includes three-year college and postgraduate education, "senior high" includes two-year vocational and technical schools, “junior” includes junior high school and below. All wages are in 1988 yuan. Table 2 presents wages in logarithm by educational levels. We find that wages of all three educational levels increased over the period, the college educated gained the most, followed by senior high school. Those with junior high school and below gained the least amount. To control for other factors that influence wages, we run regressions of wages against education levels and other personal characteristics (years of potential experiences and the square term, sex, provincial dummy variables). The resultant wage differentials between educational levels and their changes in 1990-1995 and 1995-2000 are reported in Table 3.

As can be seen from Table 3, the wage differentials between college education and senior high school education and between senior high school education and junior high school education and below both experienced dramatic increases in the 1990s. However, there were some notable differences between 1990-95 and 1995-2000 and between the two differentials. First, the wage differential widened faster between senior high school and junior high and below than between college and senior high school. Secondly, the wage differential widened faster in 1995-2000 than 1990-95. The wage differential between senior high school and junior high school started at a very small level, at 3.5%. This differential more than tripled to 11.5% in 1995 and again more than doubled to 22.8% in 2000. In comparison, the wage differential between college educated and senior high school started at a much higher level, at 22.1% in 1990, and increased at a much moderate rate, to 27.6% in 1995 and 34.1% in 2000. The goal of this paper is to explain these patterns and trends.

Table 3

III. A Conceptual Framework

Much of our conceptual framework is based on Bound and Johnson (1992) and modified to fit our context. For the sake of convenience, it is assumed that the aggregate labor force is composed of I educational groups, and there are S sectors of employment (defined by industries and ownerships).

Following Bound and Johnson (1992), the wage of education group-i (i=college, senior high, and junior high and below) in sector-s, W_{is}, can be conveniently defined as the product of the competitive wage W_{ic} , and a relative wage rent (or wage premium) in sector-s, R_{is}:

$$W_{is} = W_{ic} R_{is} \tag{1}$$

If the non-pecuniary attributes of employment in all sectors are identical and nothing causes wage to deviate from their competitive norm, the wage rent R_{is}'s would be identically equal to 1. However, to a great extent, wage differentials do exist across sectors (Krueger and Summers, 1988; Healwege, 1992).

Take the logarithm of equation (1), the logarithm wage of group-*i* in sector-*s* can be decomposed into two additive parts:

$$w_{is} = w_{ic} + r_{is}\,, \qquad (1')$$

where w_{is}, w_{ic}, r_{is} are respectively the logarithm of the real wage, competitive wage and wage rent of group-i in sector-s, namely, $w_{is}=ln(W_{is})$, $w_{ic}=ln(W_{ic})$, $r_{is}=ln(R_{is})$;

Averaging both sides of equation (1') across all sectors, we get:

$$w_i = w_{ic} + r_i = w_{ic} + \sum_s r_{is}\phi_{is} \qquad (2)$$

where $r_i = \sum_s r_{is}\phi_{is}$ is the wage rent enjoyed by group-i; w_i is the average log wage of group-*i*, $w_i = \sum_s w_{is}\phi_{is}$, ϕ_{is} is the proportion of group-i in sector-s, namely, $\phi_{is}=N_{is}/N_i$, where N_{is} is the number of group-i in sector-s, N_i is the total number of group-i.

Differentiating equation (2), we get:

$$dw_i = dw_{ic} + dr_i \qquad (3)$$

Therefore, any change in wage differentials between educational groups is caused either by changes in wage rents or by changes in competitive wage. We examine both sources in turn.

3.A Changes in Wage Rents

The change in wage rent enjoyed by educational group-I, dr_i in equation (3), can be written as

$$dr_i = \sum_s (\phi_{is}dr_{is} + r_{is}d\phi_{is}) = \sum_s \phi_{is}dr_{is} + \sum_s r_{is}d\phi_{is}$$

This decomposition has two elements: one is due to changes in the relative wage among economic sectors, $\sum_s \phi_{is}dr_{is}$, termed "wage effects"; the other is due to changes in employment distribution across economic sectors, $\sum_s r_{is}d\phi_{is}$, termed "weight effects".

Assuming that the wage rent in sector-s is identical for all educational groups, namely, $r_{is} = r_s$, considering two dimensions of sectors, industries and ownership, we further decompose the wage rent into industrial wage rents and ownership wage rents[1]

$$r_i = \sum_{s=1}^{S} r_s \phi_{is} = \sum_{j=1}^{J}\sum_{o=1}^{O} r_{jo}\phi_{ijo} = \sum_{j=1}^{J}\sum_{o=1}^{O}(r_{jo} - r_j + r_j)\phi_{ijo}$$
$$= \sum_{o=1}^{O}\sum_{j=1}^{J}(r_{jo} - r_j)\phi_{ijo} + \sum_{j=1}^{J} r_j \phi_{ij} = r_i^O + r_i^J$$

where, subscript *j* stands for industry-*j*, and subscript *o* refer to ownerhisp-*o*; r_{jo} is the wage rent rate in ownership-*o* and industry-*j*; r_j is the average wage rent in industry-*j*; ϕ_{ijo} is the fraction of group-i in ownership-o and industry-j; ϕ_{ij} is the fraction of group-i in industry-j. $r_i^O = \sum_{o=1}^{O}\sum_{j=1}^{J}(r_{jo} - r_j)\phi_{ijo}$ is the ownership wage rent, and $r_i^J = \sum_{j=1}^{J} r_j \phi_{ij}$ is the industry wage rent enjoyed by group-i.

Assuming that the industrial wage rent rate r_j and ownership wage rent rate r_o are determined independently, namely, $r_{jo} = r_j + r_o$, then the ownership wage rent enjoyed by group-i can be written as: $r_i^O = \sum_{o=1}^{O} r_o \phi_{io}$. The sectoral wage rent enjoyed by group-i can be simplified as

$$r_i = \sum_{o=1}^{O} r_o \phi_{io} + \sum_{j=1}^{J} r_j \phi_{ij} = r_i^O + r_i^J$$

Differentiating this equation and we get,

$$dr_i = dr_i^O + dr_i^J = \left(\sum_{o=1}^{O}\phi_{io} dr_o + \sum_{o=1}^{O} r_o d\phi_{io}\right) + \left(\sum_{j=1}^{J}\phi_{ij} dr_j + \sum_{j=1}^{J} r_j d\phi_{ij}\right) \tag{4}$$

Using equation (4),, we can separately estimate changes in industrial wage rent dr_i^J and changes in ownership wage rent dr_i^O, and each of these two items can be further decomposed into wage effect and weight effect.

3.B Changes in Competitive Wage

Following Bound and Johnson (1992), we decompose the change in group

[1] This assumption implies that the wage rent is only related to the characteristics of sector-s and is exogenous to worker’s education level, thus no selection effects are under consideration.

competitive wage as follows,

$$dw_{ic} = (1 - 1/\sigma) d(\ln b_i) + (1/\sigma) d(\ln D_i) - (1/\sigma) d(\ln N_i) \tag{5}$$

where dw_{ic} is the change in relative competitive wage of group i, $dlnN_i$ is the change in relative supply of group-i, $dlnD_i$ is the change in relative demand due to the shift of product demand across industries, $dln(b_i)$ is the change in relative general technical efficiency of group-i, and σ is the elasticity of intra-factor substitution among educational groups, which ranges from 0 to positive infinite.

Equation (5) states that the change in the relative competitive wage of group-*i* workers depends positively on the change in relative technical efficiency $d(lnb_i)$, negatively on the relative supply change $d(lnN_i)$, and positively on the change in the demand for products that use group-i more intensively $d(lnD_i)$. The effect of each source depends on the elasticity of the intrafactor substitution, σ.

3.C Summary: Decomposition of the Change in Relative Wage

Plugging equations (4) and (5) into equation (3), we have the final equation for decomposing the change in the relative wage of one educational group,

$$dw_i = (1 - 1/\sigma) d(\ln b_i) + (1/\sigma) d(\ln D_i) - (1/\sigma) d(\ln N_i) + (dr_i^O + dr_i^J) \tag{6}$$

This equation states that a change in wage of group-*i* relative to the mean wage or the wage of another educational group can be decomposed into four sources: changes in its wage rent, changes in relative labor supply of the group, changes in relative labor demand for the group derived from shift in product demand, and change in relative technology efficiency of group-*i*.

IV. Estimation Results

4.A. Changes in Wage Rents

Changes in Industrial Wage Rents

The discrete form of Equation (6) can be written as

$$\Delta r_i^J = \sum_j \phi_{ij} \Delta r_j + \sum_j (r_j + \Delta r_j) \Delta \phi_{ij} \tag{7}$$

The first term of the left hand is changes in industrial wage rent due to changes in relative wage levels across industries, i.e., the wage effects; the second term is due to the changes in educational composition of employment between high- and low-wage industries, i.e., the weight effects.

The share of group-*i* in industry-*j*, ϕ_{ij}, and the change can be computed directly from data, but we need to estimate wage rent of group-*i* in industry-*j*, r_j. As mentioned above, assuming that the industrial wage rent rate r_j and ownership wage rent rate r_o are determined independently, we can use the following regression to estimate the wage rent rate in industry-j,

$$\ln W_k = \alpha_0 + \sum_i \alpha_i G_{ki} + \sum_j \gamma_j S_{kj} + \sum_o \gamma_o S_{ko} + \sum_p \beta_p P_{kp} + \sum_t \beta_t T_{kt} + \varepsilon_k \qquad (8)$$

where the subscripts *k* represents the individual-*k*. $\ln W_k$ is the logarithm of individual-*k*'s real wage, G_{ki} are a set of dummy variables representing individual-*k*'s characteristics of gender, experience and education, S_{kj} stands for the dummy variables for industry-*j*, S_{ko} stands for the dummy variables for ownership-o, P_{kp} refers to the dummy variable for province-*p* and T_t is the dummy for year t,[2] and ε is the error term. The estimated coefficients on the dummies for industries, γ_j's represent the industrial wage relative to the reference group in the regression. The deviation of the estimated values for γ_j's from their mean value $\bar{\gamma}$ in each period, $r_j = \gamma_j - \bar{\gamma}$, is the estimates of the wage rent rates in industry-*j*'s, r_j.[3]

Categorization of industries in UHS varies in different years. We re-categorize the industries into 10 categories to achieve consistency over years. Estimated wage rent, r_j's, are reported in column (i)-(iii) of Table 4.

Not surprisingly, monopoly industries such as finance and insurance, transportation, postal and telecommunications services have consistently enjoyed above average wage rents while decentralized and competitive industries such as manufacturing, retail trade and food catering have below than average wages. The data also confirm anecdotal observations that government agencies and semi-governmental social service sectors (education, research, culture and mass Media and health care, sports and social welfare) have enjoyed considerable gains in wages.

Table 4

The distributions of employment across industries of each educational group are reported in column (iv)-(xii) in Table 4. It is easy to see that workers with less

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2 As mentioned earlier, each year represents three years. For example, data for 1990 has 1989, 1990 and 1991.

3 The mean of γ_j is the weighted average of the estimated coefficients: $\bar{\gamma} = \sum_j \phi_j \gamma_j$, where ϕ_j is the proportion of the workers employed in industry-*j*.

education tend to work in low-wage industries. Nearly half of workers with junior high school education or below were in manufacturing, and another 18 percent or so worked in the retail and catering industry. Over years these workers increasingly worked in the social service industry, reaching 10 percent in 2000. Although these three industries also absorbed a large share of the senior high school graduates, the percentages were relative lower. Over years, more senior high school graduates entered into high-paying sectors such as the medical care, finance and insurance, and government or semi-government agencies. For the college graduates, although nearly one quarter was employed by the manufacturing industry, nearly 40 percent entered into educational institutions and government or semi-governmental agencies that enjoyed relative high wage rents.

Over time, it is not obvious at first sight whether high-wage industries expanded or contracted, or whether workers with less education left or entered low-wage industries. In columns (ii)-(iv) of Table 5 we calculate the total effects from changes in industrial wage rents on wage differential by educational groups and decompose the effects into wage effects and weight effects according to Equation (7).

Table 5

The total effect of changes in relative industrial wage rents are all positive, indicating that changes in industrial wage rent have resulted in higher returns to education. In both periods and for both college vs. high school and high school vs. junior high school and below, wage effects dominated the weight effects, indicating that the change in the relative wage of industries is the main cause of the change in industrial wage rents. Inspecting the results more carefully yields some interesting observations. In 1990-95, the effect on the wage differential between senior high and junior high and below were similar to that between college and senior high school graduates and largely due to the similarity in wage effects which far dominated the weight effects, indicating that wage changes across industries did not favor one group over the other, and that there was little education-selective mobility across industries. However, in 1995-2000, changes in industrial rent strongly favored college educated, and this was caused not by education-biased industrial wage changes, but by intensified selection of employment into high-wage industries by the college-educated. By anecdotal evidence, the selection has taken place in two forms. One is by new job market entrants – college graduates increasingly looked for jobs on their own instead of relying on government allocation. The second is so called “jumping into the sea” –

those working in government or semi-government sectors such as universities and research organizations leave for the financial sector, for example.

Changes in Wage Rents in State-Owned Sectors

An important part of the economic transition in China has been liberalization of wage setting among state-owned enterprises (SOEs) broadly defined to include government and semi-government institutions. It is thus interesting to explore whether rents for SOEs existed independently of industry rents and how that affected wage differential across educational groups.

Similar to the estimation of industry rent, the wage rent rate in ownership-o, r_o can be estimated from running the regression (8), in which S_{ko} is just a dummy variable for SOE. The estimated r_o's are reported in column (i)-(iii) in Panel B of table 4. Employment distributions across ownerships of three educational groups are listed in column (iv)-(xii).

It is immediately obvious that state-owned sectors have enjoyed positive and large wage rents, and the ownership wage rent changed little during 1990-2000.

With the estimated wage rents and employment distribution across ownerships, we calculate the effect of changes in ownership wage rent on the relative wage of group-i, and decompose it into wage effect and weight effect by the formula,

$$\Delta r_i^O = \sum_o \phi_{io} \Delta r_o + \sum_o (r_o + \Delta r_o) \Delta \phi_{io} \tag{9}$$

The estimation results are reported in column (v) and (vii) of table 5. Results show that the change in ownership wage rent were negative but very small in 1990-95, clearly dominated by the positive effects of industrial rent. Of the limited impact, however, it is interesting to observe that the wage effects were positive, implying the wage levels in SOEs increased relative to non-SOEs during the period, but the weight effects were negative, a reflection of the fact that more educated left the state-owned sector, as obvious from Table 4. In 1995-2000, however, the wage effect became negative, indicating that the wage differential between SOEs and non_SOEs shrank, and the weight effect remained negative for the wage of senior high relative to junior high and below, but turned positive for the wage of college relative to senior high school graduates, a reflection of the fact that college-educated are returning to the state-sector.

After accounting for wage rents, ,in both periods, substantial amount of the change in wage differential across education groups remain unexplained. We now turn to changes in relative competitive wage.

4.B. Shifts in the structure of labor supply and products demand

Shift in the Structure of Labor Supply

A natural index that captures the changes in relative labor supply across groups is labor-supply-shift index, SUP_i, the proportionate change in the logarithm of group-i's share of aggregate labor force,

$$SUP_i = \Delta(\ln \phi_i^s) \qquad (10)$$

where $\phi_i^s = N_i^s / N^s$ is the fraction of group-i in total labor force.

The educational composition of labor force from the UHS is reported in column (i)-(iii) Table 6. One major limitation of the UHS data is that the surveys include only registered urban residents, and exclude migrants who do not have local urban Hukous. Because local residents and migrants increasingly compete with each other, labor supply generated from local residents is incomplete. Using census data from the same provinces which include migrants in 1990 and 2000, we re-estimate the size of labor supply in urban areas. Under the assumption that the change in the fraction of migrants is linear from 1990 to 2000, we compute the fraction of migrants in 1995. As Table 6 reports, the fraction of migrants in the labor force was 7.61% in 1990, 18.71% in 1995 and 29.81% in 2000. The composition of migrants across education levels are reported in (column (iv)-(vi) in table 7).

According to the fraction of migrants and their composition by education, we adjust labor supply by education, which are reported in the column (vii)-(ix) of table 7. Thus the index for change in relative supply of group-i, SUP_i can be calculated by equation (10). The relative values of SUP_i*'s* are reported in column (i) of Table 9.

Table 7

It is clear from table 7 that if we look at local residents alone, the rise in educational attainment has been very rapid,. However, if we include migrants, the rise is much less dramatic. In 1995-2000, the decline in the share of junior high school graduates for the local urban residents was completely offset by the inflows of migrants who posses mostly junior high school education or lower.

Consequently, it can be observed from the relative value of SUP in table 9 that, in the period of 1990-1995, both the relative supply of senior high school to junior school graduates and that of the college to senior high school graduates went up, by 14 percent and 30 percent respectively. However, in the period of 1995-2000, the situation changed drastically by the surge of immigrants, most of whom were junior high school educated. This led to a decline in the share of senior high school graduates, and resulted in a decline of 6 percent in the relative supply of senior high school graduates to the junior high school graduates or below, but the supply of the college educated relative to the senior high school increased by 15 percent.

Changes in Labor demand Due to the Shift in Product Demand

Changes in the structure of output can lead to changes in the structure of inputs. Under the assumptions that the labor productivity remains constant for all industries and labor market clears in each period, changes in employment distribution across industries should reflected the shift in the structure of product demand. Under such assumptions we follow Katz and Murphy (1992) to use the average employment growth by industry weighted by the initial employment distribution of each demographic group as an index to reflect the effect of product demand shifts on relative labor demand,,

$$EMP_i = \sum_j \Delta(\ln \phi_j)\phi_{ij} \tag{11}$$

where ϕ_j is the share of employment in industry-j; $\Delta(\ln \phi_j)$ is the proportionate change in the logarithm of employment share in industry-*j*. This index is actually the deviation of the growth rate of employment in industry-j from the average growth rate of employment across all industries.

To show the change in the structure of industries, we confine our UHS sample to the employed. The distribution of employment across industries, ϕ_j, computed from the UHS data of local residents, are reported in columns (i)-(iii) of table 8. For the same reason as in the calculation of the index of relative labor supply, these statistics do not correctly represent the structure of employment by industries in urban area, because of the exclusion of migrants from the survey. We adjust the statistics using the share of migrants and their distributions across industries calculated from the census in 1990 and 2000. The calculated fractions of migrants in worker force in urban area are in table 6, and the employment distributions of migrant workers across industries are listed in column (iv)-(vi) in table 8. The adjusted employment distributions of all urban workers are reported in columns (vii)-(ix) in table 8. The computed $\Delta(\ln\phi_j)$ for the urban area are in columns (x) and (xi) of table 8.

We can see from the values of $\Delta(\ln\phi_j)$ that industries such as education and media, and semi-government organizations experienced a relative contraction, especially during 1995-2000, which employ the college educated more intensively. This is expected to cause a decline in the relative demand for college educated workers.

Table 8

After obtaining the values of $\Delta(\ln\phi_j)$, the index EMP_i can be computed as a proxy of the change in the structure of labor demand, $d(\ln D_i)$, which is assumed to be caused by changes in the structure of product demand. The relative values of EMP_i between educational groups are reported in columns (iii) (iv) in Table 9. It can be seen that the relative values of this index are all negative for both 1990-95 and 1995-2000, which means that the shift in product demand caused a relatively larger demand for unskilled workers.

Product-demand-shift index EMP_i captures the growth rate of employment in group-*i* due to the deviation of employment growth rate of industry-*j* from the mean employment growth rate in all industries. Changes in relative employment growth rates among industries, however, could be caused not only by the product-demand structure but also by changes in labor supply structure, which in turn may cause bias in the decomposition of relative wage changes. Thus, it is necessary to net out or mitigate the effect of changes in the relative supply of the different groups.

An alternative approach that could avoid this possible bias, as used by Bound and Johnson (1992), is to estimate a discrete version of product-demand-shift index, DEM_i:

$$DEM_i = \Delta(\ln D_i) = \sum_j \phi_{ij}\Delta(\ln x_j) \tag{12}$$

where x_j is a variable that could be simply explained as the relative demand for products produced by industry-j, which is decided by the consumer's preference. But it can not be observed.

Although $\Delta(\ln x_j)$ is unobservable, Bound and Johnson (1992) approximate this index by estimating the unknown coefficients $d\ln x_j$ in the following equation,

$$d(\ln\phi_{ij}) = (1-\phi_{ij})d(\ln x_j) - \sum_{k\neq j}\phi_{ik}d(\ln x_k) + (\sigma-1)[d(\ln(b_{ij}/b_i))] \tag{13}$$

where the subscript i stands for gender-experience-educational group-i, and i=1…24; the subscript j stands for the industry-j, and j=1…10; ϕ_{ij} and x_j are the same as defined above. b_{ij} is the an index of the technical efficiency of group-i in industry-j; b_i is the average technical efficiency of group-i across all the industries; $d(\ln b_{ij}/\ln b_i)$ indicates the deviation of the growth rate of technical efficiency in industry-j from the average growth rate of technical efficiency for group-i. If the technical changes are uneven across industries and for some groups, that is, the technical efficiency for certain group in certain industry is obviously faster or slower than others, the mean of $d(\ln b_{ij}/\ln b_i)$ will not equal to 0. If we assume that the technical changes are even across industries for all the groups, the mean of $d(\ln b_{ij}/\ln b_i)$ will equal to 0, and the last term in this equation could be treated as a random error with the mean being 0. Under this presumption, we can obtain the unbiased estimate for $d\ln x_j$ by running equation (13) by OLS. The estimated value of $d\ln x_j$ actually picks up employment growth in each industry as a deviation from the weighted rates of growth across demographic groups of its initial employment distribution.

The estimated results are reported in columns (xii)-(xiii) of table 8. Based on these estimates for $\Delta(\ln x_j)$, the product-demand-shift index, DEM_i's, are calculated by equation (12). The results are reported in columns (v) and (vi) of table 9.

Table 9

Similar to the relative values of *EMP*'s, nearly all of the relative changes in *DEM*'s are negative, implying that changes in products demand across industries caused the relative demand for more educated labors to decrease. Part of the change in production may result from international trade – because China has more abundant supply of less-educated workers, the pursuit of this comparative advantage leads China to expand production that use low-skilled labor more intensively. This leads to the increase in relative demand for low-skilled workers, which is opposite to the situation in the U.S. during the 1980s. However, another part of the story may originate from China's own structural transition from a planned economy to a market-oriented economy. In this transition process, all the enterprises, both the fast developing non-state owned sectors and the more marketized state-owned sectors, have stronger stimulus to seek the maximum of profits than before. Thus the inputs that are more abundant and less expensive are increasingly being employed in the production.

4.C Skill-Biased Technical Change

Generally speaking, technological progress could occur in a particular industry or in all industries, thus, skill-biased technical changes are of two types: industry-specific technical change and general technical change, both have the effect of raising relative demand for some skill groups but the mechanisms are different. The former occurs in some specific industries and affects the technical efficiency of or relative demand for certain skill group in these specific industries; the latter affects the relative demand for a particular skill group in all industries.

Test for the Existence of Industry-Specific Technical Change

In the estimation of $\Delta(\ln x_j)$ above, we treat the effect of industry-specific technical change of each group, $(\sigma-1)[d(\ln(b_{ij}/b_i))]$ --the last term in equation (13) --as a random error. As mentioned above, this is equivalent to assuming that the growth rate of technical-efficiency parameter for group-i workers in industry-j, $d(\ln b_{ij})$, is equal to the weighted average for that group, $d(\ln b_i)$, plus a random error; in other words, there is no significant differences in the growth rate of technical-efficiency parameter for each group across all industries. However, that might not be the case. In the U.S., it has been suggested that the effects of spurts of innovation on the relative demand for different groups may vary across industries (Bound and Johnson, 1992). If the presumption for equation (13) does not hold, the estimation for $d\ln x_j$ could be biased, because a faster technology progress in some industries could cause a larger increase in the demand for labors in these industries, which would lead to certain correlation between employment distribution and the error term. Therefore, we should test whether there exists the effect of industry-specific technical change.

To clarify the question, following the illustration by Bound and Johnson (1992), we assume that, for a subset of the demographic groups, marked by *I'*, the growth rate of the efficiency parameters in some specific industries, marked by J', in which a certain new technology was introduced, may differ from their average growth rate in other industries. In this setting, it is reasonable to suppose that the growth rate of technology efficiency of group-*i* in industry-*j* can be written as follows,

$$d(\ln b_{ij}) = \begin{cases} c_{i0} + c_{i1} & \text{if } j \text{ in } J' \text{ and } i \text{ in } I' \\ c_{i0} & \text{otherwise} \end{cases} \tag{14}$$

where the average growth rate in technical efficiency of group-i across all industries other than specific industries J' is assumed to be c_{i0}; the difference between the growth rate of technical efficiency of group-i in specific-industries J' and the average value in other industries, c_{i0}, is assumed to be a constant, c_{i1}. If there is no significant influence of industry-specific technical efficiency change on some specific groups, the average growth rate of technology efficiency for each group should be all equal to their common component, c_{i0}.

Then, the average growth rate of technology efficiency for group-*i* is,

$$d(\ln b_i) = \begin{cases} c_{i0} + \sum_j \phi_{ij} c_{i1} = c_{i0} + \Phi_{iJ'} c_{i1} & \text{if i in I'} \\ c_{i0} & \text{if i not in I'} \end{cases} \tag{15}$$

where $\Phi_{iJ'} = \sum_{j \in J'} \phi_{ij}$ is the proportion of specific group-i's employment in specific-industries J'. Hence, the industry/group-specific technical efficiency change of group-i in industry-j is,

$$d[\ln(b_{ij} / b_i)] = \begin{cases} c_{i1}(1 - \Phi_{iJ'}) & \text{if i in I'} \\ 0 & \text{if i not in I'} \end{cases} = c_{i1} D_{I'} (D_{J'} - \Phi_{iJ'}) \tag{16}$$

Substituting equation (16) into equation (13), we get

$$d(\ln \phi_{ij}) = (1 - \phi_{ij}) d(\ln x_j) - \sum_{k \neq j} \phi_{ik} d(\ln x_k) + (\sigma - 1) c_{i1} D_{I'} (D_{J'} - \Phi_{iJ'}) \tag{13'}$$

If we know the specific industry set J' and specific groups set I', we can estimate this equation using OLS, and obtain values of $(\sigma - 1)c_{i1}$. The problem is how to identify the specific industry set *J'* and specific group *I'*. We do this by trial and error.

We first explore the possibility that manufacturing industry belongs to such an industry set. During the 1990s, manufacturing has experienced rapid technological progress. Under this assumption we explore whether we can identify groups that have faster growth rate of technology efficiency in manufacturing

A strategy to identify the specific group set *I'* is to first include all the groups as the specific group set I' in regression (13'), and exclude one by one those groups on which the coefficients are non-significantly different from zero, and keep all the groups on which the coefficients (as a proxy of $(\sigma - 1)c_{i1}$) are statistically significant different from zero, as specific groups *I'*.[4]

Incidently, the result shows that there is no specific group whose growth rate of technology efficiency in manufacture is different from that in other industries. The

[4] Because $\sigma>0$, the term $(\sigma\text{-}1)c_{i1}$ should be different from zero, under the assumption that group-*i* has different growth rate of technology efficiency across industries(namely, $c_{i1} \neq 0$).

p-value for the joint exclusion test that all the 24 demographic groups are not in the specific group set I' is 0.84 for the period 1991-1996, and 0.36 for the period 1996-2001.

We also tried other industries such as construction, transportation/post/ telecom, health care/sports/social welfare, education/culture/arts/radio and television, finance/insurance as specific industry set J', separately and jointly. All the results failed to show that there is any significant industry/group technology effect. We take this as evidence that all groups in our sample have the same growth rate of technology efficiency across all industries. Another possibility is that our classification of industries is too broad to capture industry specific technical change that bias against a certain educational group.

Since there is no industry/group specific technology effects, the estimate for $d(lnx_j)$ is unbiased by running the randomized equation (13') by OLS, in which the last term $(\sigma-1)[d(\ln(b_{ij}/b_i))]$ is treated as a random error.

One possible explanation of the nonexistence of the industry-group-specific technical change is that, during the 1990s, technical changes occurred simultaneously with the economic reform that promoted efficiency in all sectors of the economy,, so the resulted change in technical efficiency in this period were not confined to certain industries.

General Technical Change

Since we assume away industry-specific technical change that bias against some educational group, all the remaining effect of technical change belongs to the effect of general technical change $(1-1/\sigma)d(\ln b_i)$. It is difficult to directly estimate this term, because b_i is unobservable.

The effect of the general technical change on the relative wage of an educational group can be approximated by the difference between the change in competitive wage dw_{ic} and the effect of the change in the relative net supply by equation (5).[5] In order to estimate the net supply, we need to obtain the estimate for the intra-factor elasticity of substitution $\hat{\sigma}$.

In estimating the intra-factor elasticity of substitution σ, there are a few choices.

[5] Although the change in net supply is written as $d\ln NS_i(t) = d\ln N_i(t) - d\ln D_i(t)]$, this is actually not the indicator for the change in net supply, because the indicator, *dlnD(t)* only covers the change in labor demand due to the change in production structure, which is only part of the change in labor demand. Another reason is that the indicator, dlnD(t), has a high possibility to be a downward biased measure of demand shift in favor of groups with relative wage increase (Katz and Murphy, 1992).

One is a strategy adopted by Bound and Johnson (1992), which employs the randomized second-differenced equation for market wage. To illustrate, take the first order difference of equation (5)).

$$d^2 w_{ic} = \beta_0 + \beta_1 d^2 \ln NS(t) + \varepsilon \qquad (17)$$

where $\beta_0 = (1 - 1/\sigma) d^2 \ln b_i(t)$ is assumed to be a constant, $d^2 \ln NS(t) = d^2(\ln N_i(t) - \ln D_i(t))$, $\beta_1 = 1/\sigma$, ε is the random error. [6]

A shortage in estimating this regression is that the number of observations for the estimation is equal to the number of gender-experience-educational groups, 24, which is obviously too small to makes the results very sensitive to outliers. The estimated coefficient is $\hat{\beta}_1$= -0.098 (se=0.066). The estimated elasticity of substitution, $\hat{\sigma}$ is about 10.22, which seems implausibly large. This could be caused by some outliers in the small number of cross-sectional observations in this regression.

We adopt a more general strategy similar to Katz and Murphy (1992) in estimating the elasticity of intra-factor substitution by by running a time series linear regression as follows,

$$\ln(W_i(t)/W_{i-1}(t)) = \alpha_0 + \alpha_1 \ln(N_i(t)/N_{i-1}(t)) + \alpha_2 t + \varepsilon \qquad (18)$$

Where *i* refers to the senior high school or college, and comparatively, *i-1* refers to the junior high school or senior high school; $W_i(t)/W_{i-1}(t)$ is the relative wage of educational group-*i* to group-*i-1* in year-*t*; $\ln(N_i(t)/N_{i-1}(t))$ is the relative supply of educational group-*i* to group-*i-1* in year-t in urban area; and $\alpha_1 = -1/\sigma$.[7]. The estimate for elasticity of intrafactor substitution $\hat{\sigma}$ can be easily computed from the estimate for $\hat{\alpha}_1 = 1\hat{/}\sigma$.

For our sample, the time *t* ranges from 1989 to 2001, and there are two comparison groups: senior high school and below versus junior high school, and college versus senior high school. OLS estimation of the equation yields an estimate

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6 Because the change in the rate of growth of technical efficiency could be different across groups, Bound and Johnson (1992) also add a few dummies in the equation to identify such difference. Their results show that five young low-education groups have a statistically significant lower value for the change in the rate of growth of technical efficiency.

7 Katz and Murphy (1992) estimate the elasticity of the substitution between college and senior high school by running a time series linear regression as follows: $\ln(w_2(t)/w_1(t)) = \alpha_0 + \alpha_1 \ln(N_2(t)/N_1(t)) + \alpha_2 t + \varepsilon$, where $w_2(t)/w_1(t)$, $N_2(t)/N_1(t)$ are respectively the relative wage of college to high school and the relative supply of college to high school labors; $\alpha_1 = -1/\sigma$, and α_2 capture the time trend of relative demand shift of college to high school. This regression comes from the simple CES technology with two factors (college and high school labors) and that the relative demand shift of college to high school labors is a simple linear time trend.

for the elasticity of intrafactor substitution of 2.722 ($\hat{\alpha}_1$=-0.367, se=0.092; for the regression, N=26, R^2 =0.85) (see table A-1).

With this estimate for the elasticity of intra-factor substitution, we calculate the effect of change in relative labor supply and the effect of change in relative demand due to the shift of product demand. After excluding these two effects, the residuals of changes in relative competitive wage should be attributed to the effect of general technical change. The estimated results are reported in columns (vii) and (xiv) of table 10.

From inspection of the estimated values of the effect of general technical efficiency (GTE) in table 10, it is easy to draw the conclusion that the changes in the structure of the $d\ln b_i$'s, are greatly favorable to more-educated groups.

It is important to note that although we interpret the source of this shift as an exogenous change in technology across all the industries, the result is also open to other interpretations, such as non-neutral institutional changes. As mentioned earlier, the labor market reform has liberalized wage-setting from one that compressed wage structure by educational levels.

4.D. Final Decomposition Results

Since we have now obtained all the estimates of parameter and indexes needed in equation (6), the change in wage premiums between education groups (column (i) in Table 10) can be quantitatively decomposed into four additive parts: the change in wage rents (column (ii)), the effect of change in relative labor supply (column (v)), the effect of change in relative demand resulting from production demand shift (column (vi)), and the effect of change in general technical efficiency (column (vii)). In addition, changes in wage rents for each group are decomposed into changes in industrial wage rents (column (iii)) and changes in ownership wage rents (column (iv)).

Table 10

The decomposition reveals some interesting results. First, the rise in relative technical efficiency that raised the demand for workers with more education accounted for the most part of the increased wage differential between the education groups. There may be a few sources of the changes in general technical efficiency. One possibility is that during the 1990s, technical changes that happened across all industries are biased toward more educated workers, which lead to a greater increase in their productivity and demand. The second explanation is that the institutional transition towards the market economy enables more educated workers to become more productive (Park et al., 2004). It is also possible that the effect can not be fully attributed to technical efficiency. Given efficiency, the labor market reform allows or forces higher pay for more educated and productive workers.

Second, the changes in relative wage rent across industries are another important source for the enlarging wage differentials between educational groups. This implies that more educated workers, especially the college educated workers during 1995-2000, have a higher probability to work in industries that enjoy monopoly rents or government protection.

Third, both changes in relative labor supply and the shift in product demand served to negate the rising wage differential between education groups except for the relative supply of senior high school to junior high school graduates during 1995-2000. The shift in labor supply played a more important role than the shift in product demand in magnitude. Because more migrants, most of whom are junior high school educated, flowed into urban area during the period of 1995-2000, there is a decrease in relative supply of senior high school to junior high school graduates, which cause a positive effect of the change in their relative supply as shown in column (v).

Fourth, changes in product demand are in favorite of less educated groups. This trend seems strengthened during the late 1990s. This may be caused by the enlarging international trade, which led to a shift of demand toward unskilled labor-intensive products, and caused an increase in relative demand for lower educated workers.

V. Conclusions and Discussions

In this paper we analyze reasons behind the rapid increase in wage differentials across educational groups in urban China in the 1990s. We examine the following four explanations: changes in industrial wage rents, shift in labor supply, shifts in product demand and the change in relative technical efficiency. Results show that the changes in relative technical efficiency accounted for most of the rise in return to education. The changes in technical changes could be caused by both the skill-biased technical changes and skill-biased institutional changes. The increases in relative supply of more educated workers and the shift in product demand towards less skill-intensive production reduce the growth in their relative wage; however, this effect is more than offset by the effect of the increases in wage rents and in the average technical efficiency of more educated workers.

It should also be noted that our classification of industries is very broad due to data limitation. This may have several implications for our estimations. First, the estimate of the effect of changes in industrial wage rents may be biased downward because some effects between industries effects could be counted as within-industry effects. Secondly, the effect of shifting product demand may also be downward biased for the same reason. Thirdly, the effects of general technical changes may be estimated with an upward bias. Therefore, more accurate estimations are desirable if finer data become available.

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Table 1 UHS Sample in Six Provinces

year	Sample size
1989	6007
1990	6574
1991	6574
1992	8350
1993	7472
1994	7267
1995	7353
1996	7219
1997	7373
1998	7146
1999	7037
2000	7350
2001	6618

Table2 Wage by education groups, 1990, 1995 and 2000 (in logarithm, 1988 yuan)

	1990	*1995*	*2000*
Junior high school and below	7.38	7.66	7.79
Senior high school	7.43	7.81	8.10
college and above	7.63	8.09	8.38

Table 3 Wage Differentials and Changes 1990, 1995, 2000

	Wage Differential			Changes	
	1990	1995	2000	1990-1995	1995-2000
Senior High vs. Junior High and Below	0.035	0.115	0.228	0.080	0.113
College vs.Senior High	0.221	0.276	0.341	0.056	0.065

Table 4 Wage Rents and Employment Distribution by Industry and Ownership

	Wage rent			Employment Distribution								
				Junior high and below			Senior high			College		
	1990	1995	2000	1990	1995	2000	1990	1995	2000	1990	1995	2000
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
A. Industries												
Manufacture	-0.006	-0.045	-0.081	51.00	50.65	45.02	37.02	35.83	36.41	27.07	27.09	24.49
Construction	0.060	0.077	-0.020	3.43	4.96	4.26	2.13	3.82	3.44	1.26	2.98	3.42
Transportation, Post and Telecom Services	0.068	0.100	0.123	8.38	6.81	8.76	6.46	6.80	7.61	3.43	3.61	4.24
Wholesale/Retail Trade & Catering Services	-0.024	-0.091	-0.116	18.57	18.55	17.90	15.07	16.82	16.35	6.11	8.13	8.50
Public Utility Management and Social Services	-0.009	0.089	-0.030	4.68	6.11	10.23	3.89	4.81	9.44	1.38	2.73	5.41
Health Care, Sports and Social Welfare	0.046	0.083	0.181	2.18	1.89	2.00	7.21	6.35	5.35	8.08	6.32	6.02
Education, Research, Culture and Mass Mdia,	-0.012	0.050	0.167	2.94	3.42	3.07	10.55	9.42	7.06	26.67	21.24	17.59
Finance and Insurance	0.100	0.253	0.212	0.62	0.49	0.73	2.71	3.60	3.08	2.32	3.07	6.14
Government Agencies and Social Organizations	-0.010	0.042	0.118	4.85	4.99	4.26	12.29	11.02	8.39	21.08	22.96	22.15
Geological Exploration and Other Industries	-0.053	-0.037	-0.125	3.35	2.12	3.76	2.68	1.53	2.87	2.60	1.87	2.03
B. Ownerships:												
Non-SOE	-0.128	-0.139	-0.116	0.34	0.32	0.38	0.17	0.19	0.27	0.05	0.08	0.15
SOE	0.040	0.038	0.043	0.66	0.68	0.62	0.83	0.81	0.73	0.95	0.92	0.85

Table 5 Changes in relative wage and wage rents for educational groups

	Δ wage differential	Industrial wage Rent			Ownership wage Rent			Total wage Rent
		wage effect	Weight effect	Total	wage effect	Weight effect	Total	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
1990-1995								
Senior High vs. Junior High and Below	0.08	0.02	0.002	0.021	0.001	-0.005	-0.004	0.017
College vs. Senior High	0.056	0.02	-0.003	0.018	0.001	-0.003	-0.002	0.016
1995-2000								
Senior High vs. Junior High and Below	0.113	0.023	-0.017	0.006	-0.002	-0.005	-0.007	-0.001
College vs. Senior High	0.065	0.03	0.012	0.042	-0.002	0.003	-0.001	0.041

Table 6 Share of Migrants in in the Labor Force and the Employed in Urban Areas in 6 Provinces

	1990	1995	2000
	(i)	(ii)	(iii)
Labor force	7.61	18.71	29.81
Employed	7.78	19.90	32.01

Note: * Under the assumption that the increase of migrants is linear during 1990-2000, the estimation of the fractions of migrants in 1995 is based on the following equation: fmig1995=fmig1990+(fmig2000-fmig1990)/10*5, where fmig1990, fmig1995 and fmig2000 respectively stand for the fraction of migrants in 1990,1995 and 2000.

Table 7: The Composition of Labor Force in Urban Areas

	Local residents			Migrants			All		
	1990	1995	2000	1990	1995	2000	1990	1995	2000
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
Junior High and Below	49.57	38.73	33.32	80.74	79.27	77.79	51.94	46.32	46.58
Senior High	37.15	40.86	41.71	17.20	17.50	17.80	35.63	36.49	34.59
College	13.28	20.41	24.97	2.07	3.24	4.41	12.43	17.20	18.84

Table 8 adjusted Proportionate Employment Changes ($\Delta(\ln\phi_j)$) and Derived Demand Indexes ($\Delta(\ln x_j)$) by Industry for 1990-1995 and 1995-2000 the change in the structure of industries

Industries	Local Urban worker			Migrant workers			Employed in urban area			$\Delta(\ln\phi_j)$		$\Delta(\ln x_j)$	
	1990 (i)	1995 (ii)	2000 (iii)	1990 (iv)	1995 (v)	2000 (vi)	1990 (vii)	1995 (viii)	2000 (ix)	1990-1995 (x)	1995-2000 (xi)	1990-1995 (xii)	1995-2000 (xiii)
Manufacture	42.60	39.69	36.12	42.48	50.80	59.12	42.59	41.90	43.48	-0.016	0.037	-0.009	-0.053
Construction	2.65	4.08	3.70	18.47	13.25	8.03	3.88	5.91	5.09	0.419	-0.149	0.472	-0.077
Transportation, Post and Telecom Services	7.00	6.14	7.11	4.92	3.75	2.58	6.84	5.66	5.66	-0.189	0.000	-0.097	0.192
Wholesale/Retail Trade & Catering Services	15.59	15.67	14.82	18.82	19.25	19.67	15.84	16.38	16.37	0.034	-0.001	0.060	-0.009
Public Utility Management and Social Services	3.94	4.88	8.65	6.78	7.11	7.44	4.16	5.32	8.26	0.246	0.440	0.273	0.614
Health Care, Sports and Social Welfare	4.83	4.63	4.43	0.88	0.73	0.58	4.53	3.86	3.20	-0.160	-0.187	-0.162	-0.104
Education, Research, Culture and Mass Media,	8.97	9.58	8.50	4.98	3.21	1.44	8.66	8.31	6.24	-0.041	-0.287	-0.127	-0.231
Finance and Insurance	1.62	2.30	3.11	0.14	0.20	0.27	1.50	1.88	2.20	0.224	0.157	0.183	0.122
Government Agencies and Social Organizations	9.80	11.20	10.62	2.23	1.46	0.70	9.21	9.26	7.44	0.006	-0.219	-0.024	-0.163
Geological Exploration and Other Industries	3.00	1.83	2.94	0.30	0.24	0.18	2.79	1.51	2.06	-0.611	0.306	-0.470	0.493
Total	100	100	100	100	100	100	100	100	100	-	-	-	-

Table 9 Changes in Relative Supply and Changes in Relative Labor Demand Due to Shift in Relative Product Demand across Industries

Educational groups	SUP (i)	EMP (ii)	DEM (iii)
1990-1995			
Senior High vs. Junior High and Below	0.139	-0.004	-0.02
College vs. Senior High	0.301	-0.013	-0.036
1995-2000			
Senior High vs. Junior High and Below	-0.06	-0.045	-0.027
College vs. Senior High	0.145	-0.071	-0.059

Table 10 Decomposition of the Wage Differentials Between Educational Groups

	Δ Wage Premium	Δ Wage rent			Effect of SUP	Effect of DEM	Effect of Tech
		Industry-ownership	industry	ownership			
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
1990-1995							
Senior High vs. Junior High and Below	0.080	0.017	0.021	-0.004	-0.051	-0.007	0.121
College vs. Senior High	0.056	0.016	0.018	-0.002	-0.111	-0.013	0.163
1995-2000							
Senior High vs. Junior High and Below	0.113	-0.001	0.006	-0.007	0.022	-0.01	0.102
College vs. Senior High	0.065	0.041	0.042	-0.001	-0.053	-0.022	0.099

Appendix Table A-1 Results from regression of relative wage on the relative labor supply from 1989-2001

COEFFICIENT	(1) pooled sample	(2) Senior/junior and below	(3) College/senior high
$Ln(N_i/N_{i-1})$	-0.367***	-0.205	-0.0296
	(0.092)	(0.21)	(0.18)
year	0.0255***	0.0274***	0.00905
	(0.0029)	(0.0029)	(0.0075)
D_1×year [a]	0.0000480*		
	(0.000024)		
Constant	-50.94***	-54.58***	-17.84
	(5.88)	(5.73)	(15.2)
Observations	26	13	13
R-squared	0.85	0.91	0.48
elasticity	2.722	4.881	33.75

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

a. D_1 is a dummy variable; it takes 1 if the comparison groups are senior vs. junior high school, and 0 if otherwise.