Returns to education and earnings differences between Chinese and Indian wage earners*

Olivier Bargain
University College Dublin, and
IZA, Bonn
olivier.bargain@ucd.ie

Sumon Kumar Bhaumik
Brunel University,
William Davidson Institute, and
IZA, Bonn
Sumon.Bhaumik@brunel.ac.uk

Manisha Chakrabarty
Indian Institute of Management, Kolkata
m.chakrabarty@gmail.com

Zhong Zhao
IZA, Bonn
zhao@iza.org

May 14, 2007

Abstract:
Chinese and Indian economies have expanded by over 50% in real terms over the 1990s. However, while there was a significant increase in the average earnings of wage earners in China during this period, the average earnings of their Indian counterparts remained stagnant. In this paper, using comparable earnings data for the two countries, and a common analytical framework, we address two empirical issues, namely, the trends in returns to education in the two countries between the late 1980s and the early part of the current decade, and the extent to which Indo-Chinese differences in average earnings can be explained by differences in returns to education. Our results suggest that while returns to education in China grew much more rapidly over this period than in India, this growth still does not explain satisfactorily the much faster rise in the average earnings of the Chinese wage earners. The increase in average wages in China is much more a product of an increase in average education levels than an increase in the returns to education.

Keywords: China, India, Earnings, Returns to education, Quantile Regression, Machado-Mata decomposition
JEL Categories: O15, J24, O53, P52

---

* The authors have benefited from conversations with Gary Fields and Jim Albrecht. They remain grateful to Klara Sabirianova and Yuriy Gorodnichenko for the Stata code on the Machado-Mata decomposition algorithm, and to the IZA and the CHIPS project for providing the Indian and Chinese data, respectively. Bargain and Bhaumik would like to acknowledge financial support from IZA visitor program. The usual disclaimers apply.
Corresponding author: Zhong Zao, IZA, Schaumburg-Lippe-Str, 5 – 9, 53113 Bonn, Germany, +49-228-38 94 302, zhao@iza.org.

1. Introduction

China and India are among the fastest growing developing countries in the world. While development paths have been very different in the two countries, they currently face the common challenge of sustaining the supply of skilled and semi-skilled labourers to rapidly growing industries within these economies.

Post-reform (i.e., post-1991) growth in India has relied significantly on expansion of the services sector (in particular business services, communication services and banking) and skill-based manufacturing industries like auto ancillaries and pharmaceuticals. Most of this growth was productivity-driven, as best manifested by a low elasticity of employment with respect to GDP (0.47 according to Dev, 2002). Skill-intensive growth, however, may be threatened by acute skill shortage in services and industries (Banga, 2006, Rajan and Subramanian, 2006).

In China, a significant proportion of the growth in the post-reform period (starting from 1978) can be traced back to high rates of investment, and the movement of (surplus) labourers in the agricultural sector to the expanding manufacturing sector (Cai, 2005). However, since the early 1990s, there has been a significant shift in the structure of the Chinese economy, with high technology industries and services progressively accounting for greater share of value added and employment.[1] It is increasingly being recognised that with the change in the composition of goods that are produced in China the supply of labourers with skills that are desired by the employers is lagging behind demand, resulting in skill shortage (Knight and Song, 2003).

The stylised policy prescription to the question of skill shortage involves greater supply of educational facilities. However, investment of time and resources in education is not only influenced by supply side considerations (quality and affordability of higher education) but also by expected returns (Levhari and Weiss, 1974; Altonji, 1993).[2] Not surprisingly, returns to education have been estimated for a large number of countries around the world (Psacharopoulos, 1985; Card, 1999; Psacharopoulos and Patrinos, 2004), including China (e.g., Yang, 2005) and India (e.g., Saha and Sarkar, 1999). However, comparative studies of returns to education in countries that are competing on the basis of labour skills are conspicuous by their absence. We address these questions in the present paper by estimating

[1] For example, between 1995 and 2002, the share of textiles in industrial output declined from 9.5% to 6.5%, while the share of electronics goods rose from 5% percent to 11.5%. Similarly, between 1990 and 2002, the share of the services sector, which is dominated by skill-intensive industries like finance and telecommunications, increased from 23% to 33.5% of GDP, and from 11.7% to 28.6% of employment (Cai, 2005).

[2] The positive link between private returns on education and demand for education has been demonstrated in the context of India (Munshi and Rosenzweig, 2003).

earnings equations for workers in the formal sector in both India and China, using quantile regression models that are more suitable than ordinary least squares (OLS) for countries where heterogeneity within the labour force in terms of earnings and characteristics is significant. In addition, we examine the extent to which differences in returns to education explain differences in earnings between these two countries.

Our results indicate that the gap in average earnings, which was in favour of the Indian wage earners in the late-1980s, declined rapidly over time, especially for the people in the upper earnings quantiles. However, this shift cannot be satisfactorily explained in terms of differences in returns to education. While returns to education rose significantly in China, especially between periods 1 and 2, the returns in India continued to be higher in all three periods. The main driver of the faster rise in the average earnings of the Chinese wage earners was the rapid improvement in the average education level of the Chinese work force.

The rest of the paper is structured as follows. In section 2, we report the nature of the data and the associated descriptive statistics. Wage estimations, and returns to education in particular, are presented in section 3. Section 4 provides the results of the decomposition analysis. Section 5 concludes by discussing policy implications.

2. Data description

Our empirical exercise is based on earnings data for formal sector employees in China and India. The Chinese data are obtained from the 1988, 1995 and 2002 waves of the China Household Income Project (CHIP).[3] Based on the large sample used by the National Bureau of Statistics, each of the three surveys gathers information from over 20,000 individuals, covering both rural and urban regions in eleven provinces in China and resembling the actual distribution of populations across these regions (Demurger et al., 2006). After accounting for missing values and restricting the sample to urban wage earners in the 21-60 age group, the sample sizes for 1988, 1995 and 2002 are 16,519, 11,870 and 8,164, respectively.

The data on the Indian wage earners are obtained from the 1987, 1993 and 2004 rounds of the National Sample Survey (NSS). These pan-Indian surveys are organised by the Central Statistical Organisation, and use a stratified random sampling scheme to collect the data. The stratification is along geographical lines, with each state, as well as each district within a state, getting adequate representation (see Kijima, 2006). The data provides complete earnings information only for wage earners so that the natural restriction on self-employed

[3] The CHIP project was jointly set up in 1987 by the Institute of Economics of the Chinese Academy of Social Sciences, the Asian Development Bank and the Ford Foundation; it also received support from the East Asian Institute of Columbia University.

and casual workers is automatic. Accounting for the same age selection, the size of the Indian sample was 22,480 in 1987, 21,681 in 1993, and 10,186 in 2004.

We use the information provided in the CHIPS and NSS data to construct measures of weekly earnings and render them comparable across countries and across years by transformation all earnings into 2000 PPP US dollar equivalent, using the World Development Indicators on consumer price indices and PPP conversion factors (details available upon request). We also render comparable the levels of education across the two countries. The CHIPS data provide information on the years of schooling while NSS data report categories of educational attainment of the respondents. We use the former to construct categorical education variables for China that are comparable with those for India.[4]

Table 1: Descriptive statistics

	India			China		
Period	1	2	3	1	2	3
No of observations	22,480	21,681	10,186	16,519	11,870	8,164
Age	37.2	37.7	37.4	38.0	39.5	40.9
Female	0.15	0.16	0.18	0.47	0.48	0.44
No or primary education	0.33	0.26	0.20	0.12	0.06	0.02
Middle secondary education	0.13	0.14	0.16	0.38	0.30	0.21
High secondary education	0.29	0.31	0.34	0.36	0.40	0.40
College	0.24	0.29	0.30	0.14	0.24	0.37
Mean weekly earnings	89	104	140	52	70	134
Median weekly earnings	74	90	104	47	64	116

Period 1 is 1987 for India (1988 for China); period 2 is 1993/4 for India (1995 for China); period 3 is 2004 for India (2002 for China)
Selection: urban workers in formal sector, aged 21-60. Earnings are expressed in 2000 PPP international USD.

The descriptive statistics for the CHIPS/Chinese data and the NSS/Indian data are reported in Table 1. They indicate that in all three periods, our samples include Chinese and Indian wage earners of comparable age, with a Chinese worker being only marginally older than her Indian counterpart. Women's participation in the formal sector work force in China is much higher than that in India.[5] On average, Chinese workers in the urban formal sector are more educated than the corresponding labour force in India. The proportion of labourers

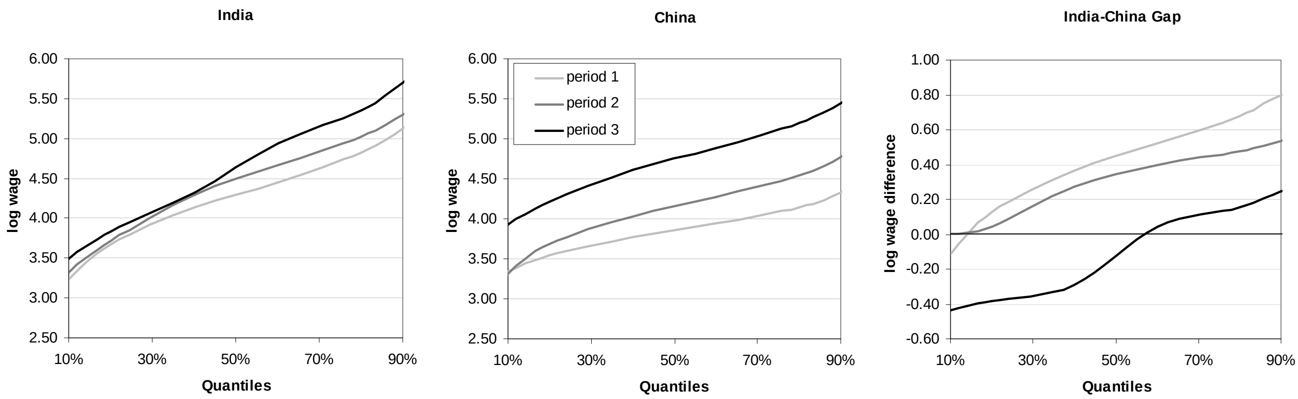
[4] Specifically, Chinese labourers with less than or equal to 6 years of education are considered to have either no education or primary education, those with 7-9 years of education are considered to have middle secondary education, those with 10-12 years of education or with vocational training beyond 9 years of schooling are considered to have higher secondary education, and those with more than 12 years of education are classified as having college education. Greater details about the rationale for the choice of these education categories, as originally designed for India, can be found in Bhaumik and Chakrabarty (2007).

[5] This is consistent with much higher female literacy in China (86% in 2002) than in India (48% in 2003).

with tertiary education is comparable across the two countries but only a very small proportion of the Chinese has no or little education in this selection (12% in period 1 and just 2% in period 3), while the proportion is substantially higher in India (33% in period 1 and 20% in period 3). Correspondingly, the proportion of people with middle secondary and higher secondary education is higher in China than in India. Since public outlays on education in China and India were similar during the mid 1990s,[6] at least part of the explanation should lie in the demand for education, which is partly an outcome of rising returns to education.

Table 1 also reports mean and median earnings of Indian and Chinese wage earners during the three periods. It is easily seen that the compounded annual growth rate of average earnings was twice as large in China as in India between periods 1 and 2 (4.3% versus 2.2%), and three times larger between periods 2 and 3 (9.6% versus 3%). Median earnings in the two countries followed a similar pattern. In both countries, median earnings were lower than mean earnings, indicating the presence of large outliers in the upper tails of the earnings distributions.

Figure 1: log-wage distribution (deciles)



These two aspects of earnings are highlighted in Figures 1 and 2, respectively. Figure 1 clearly reflects the faster wage growth in China. In periods 1 and 2, the Indo-Chinese difference in earnings is positive for nearly all deciles of the earnings distribution. However, by period 3, the earnings gap had turned in favour of China for the lower half of the distribution, and was significantly reduced for the upper deciles. Figure 1 also indicates that earnings inequality was higher in India than in China; the Kuznets ratio was clearly higher for

[6] Available data indicate that in the mid 1990s both China and India spent about 12% of their respective (consolidated) government budgets on education (Bray, 2002), and the distribution of recurrent expenditures across pre-primary and primary, secondary and tertiary education levels were very similar between the two countries (36.9%, 31.5% and 16.5% in China and 38.4%, 26.1% and 13.6% in India).

the former than for the latter.[7] However, there was a noticeable increase in earnings inequality in China between periods 2 and 3. This is consistent with available evidence on income inequality in the two countries (Meng, 2004; .Banerjee and Picketty, 2005).

Figure 2: wage distribution (density)

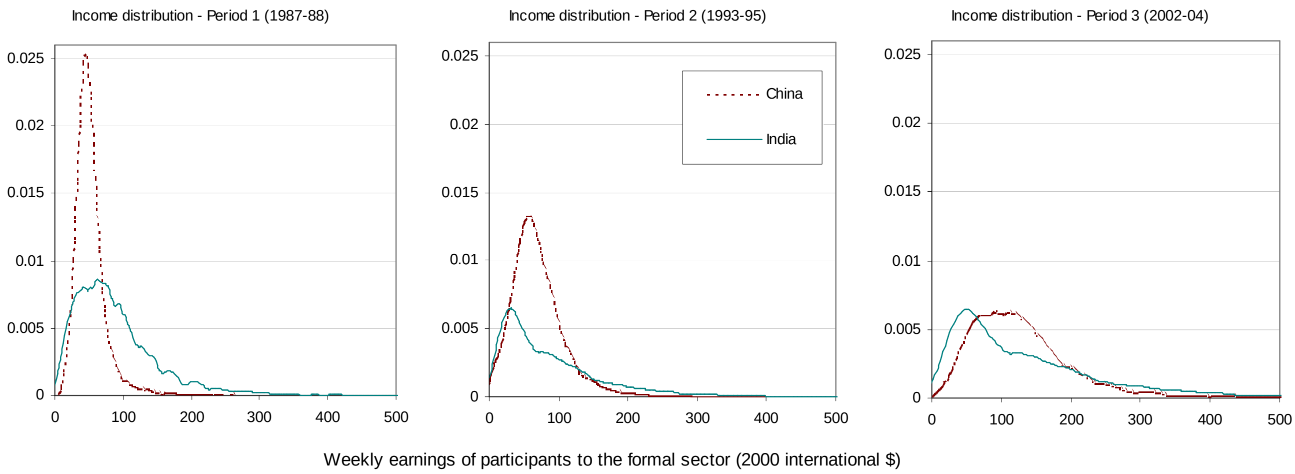


Figure 2 confirms that earnings of wage earners in China were rising faster than those of their Indian counterparts. In period 1, a very significant proportion of the workers in the Chinese sample earned less than the median Indian worker. By period 2, however, while there is some sign of a greater proportion of the Indian workers migrating towards the upper tail of the distribution, this migration is much more pronounced for the Chinese workers. Finally, by period 3, there are a smaller proportion of the Chinese wage earners in the lower tail of the distribution, compared with Indian wage earners, and, correspondingly, a greater percentage of Chinese workers in the middle earnings range than Indian workers. The Indians continue to dominate the upper tail of the distribution.

The descriptive statistics indicate that (a) there was an increase in average educational attainment and average earnings of both Chinese and Indian wage earners, and (b) the rate of growth of both education and earnings was faster among the Chinese workers than among the Indian workers. In other words, it would be reasonable to hypothesise that the changes in earnings between Chinese and Indian wage earners should be significantly explained by changes in educational attainment and returns to education, even though it would be difficult to predict *ex ante* which of these play a greater role on explaining changes in Indo-Chinese earnings differences. We revisit this issue later in the paper.

[7] The Gini for the Chinese sample increased from 24.8 to 30.3, and further to 32.2 in period 3. The Gini for India – 36.9, 38 and 43.6 – was rising over time as well, and was higher than that of China in each of these periods. 36.9 to 38 for India.

3. Earnings equation

As mentioned earlier, our first endeavour is to estimate returns to education in China and India, using comparable data and specifications. Following the bulk of the literature, we estimate separate Mincer equations for workers in India and China. The model takes the form:

$$\ln Y = \alpha_0 + \alpha_1 AGE + \alpha_2 AGE^2 + \sum_i \gamma_i EDUC_i + \sum_j \delta_j CONTROLS_j + \varepsilon \qquad (1)$$

where age is a proxy for experience;[8] as described in the previous section, education dummies correspond to no/primary education (omitted category), middle secondary education, high secondary education, and college (or tertiary) education. The control variables include gender (female = 1) and dummy variables for the three youngest age cohorts (less than 23, 23-28 and 28-35).[9] Controlling for cohort effects helps to capture structural changes in the labour market over time and improve the fit of the model (Lemieux, 2006); indeed, differences in entry wages may be observed for workers with similar entry-level skills but belonging to different cohorts.

In addition to OLS estimations, which focus on mean effects, we also perform quantile regression (Koenker and Bassett, 1978) to study the effects of covariates on earnings at different points of the conditional distribution. Precisely, we carry out quantile regressions for the 1st, 2nd, 4th, 6th, 8th and 9th deciles of the log- earnings distributions of each country. Note that we do not account for selection bias, i.e., the possibility that the workers in our sample did not become wage earners randomly but on account of some individual and household characteristics, in our estimation.[10]

Estimates of the Mincer equations for China and India are reported in Tables 2. It can be seen that females in both countries earn lesser than their male counterparts, and it is also evident that gender discrimination is higher in lower quantiles. Further, not surprisingly,

---

[8] Often, a proxy measure for experience is estimated by subtracting years of schooling and years prior to school enrolment (6-7 years) from age. However, since the Indian data do not provide information about years of schooling, we cannot undertake this exercise in this paper.

[9] A full breakdown of result by gender is available upon request to the authors. A specification where all variables vary with gender actually dominates the specification at use in the paper. However, given that our objective is to compare returns to education in China and India, as opposed to an analysis of gender differences in returns to education, we abstract from that analysis in this paper.

[10] To begin with, individual workers in developing countries with surplus labour often do not have the ability to rationally choose between forms of employment on the basis of relative marginal returns to their characteristics; choice of sectors and types of occupation is often accidental and driven by patterns of labour demand (Fields, 2005). Second, given that we have cross-section data for both countries for each time period, it is difficult to identify variables that can be used to identify a model with a selection equation and an earnings equation. Finally, despite an early attempt by Albrecht et al. (2006), extending the Machado-Mata to account for selection is as yet not common practice.

gender discrimination is lower in China than in India; gender equality is known to greater in East Asia than in South Asia (King et al. 2000). The regression estimates also suggest that the age-earnings (or experience earnings) profile in both countries is quadratic, with an inverted-U shape. As such, this is consistent with age/experience-earnings profiles observed in other countries. However, a closer examination of the coefficient estimates indicate that there are significant inter-country differences as well as differences in the age-earnings profile in China over time. In Figure 3, we report the age-earnings profiles generated from the OLS estimates reported in Table 2. The graphs indicate that returns to age (or experience) was higher, on average, in India than in China, except in period 2, and that the returns to age was much higher in China in period 2 than in the other periods.

Table 2: Estimates of Mincer equation

Period 1

Coeff.	India							China						
	OLS	10%	20%	40%	60%	80%	90%	OLS	10%	20%	40%	60%	80%	90%
age	0.10 ***	0.15 ***	0.13 ***	0.11 ***	0.09 ***	0.08 ***	0.05 ***	0.06 ***	0.07 ***	0.05 ***	0.04 ***	0.05 ***	0.06 ***	0.06 ***
age2 /1000	-0.982 ***	-1.56 ***	-1.303 ***	-1.021 ***	-0.804 ***	-0.679 ***	-0.398 ***	-0.547 ***	-0.624 ***	-0.43 ***	-0.364 ***	-0.388 ***	-0.567 ***	-0.572 ***
female	-0.44 ***	-0.85 ***	-0.66 ***	-0.41 ***	-0.27 ***	-0.23 ***	-0.22 ***	-0.13 ***	-0.16 ***	-0.12 ***	-0.10 ***	-0.10 ***	-0.10 ***	-0.14 ***
mid-secondary	**0.22** ***	**0.24** ***	**0.26** ***	**0.22** ***	**0.20** ***	**0.15** ***	**0.14** ***	**0.08** ***	**0.19** ***	**0.13** ***	**0.08** ***	**0.05** ***	**0.02** *	**-0.04** *
higher secondary	**0.57** ***	**0.63** ***	**0.63** ***	**0.56** ***	**0.52** ***	**0.47** ***	**0.47** ***	**0.13** ***	**0.26** ***	**0.18** ***	**0.13** ***	**0.08** ***	**0.07** ***	**0.01**
college	**0.97** ***	**1.04** ***	**1.04** ***	**0.96** ***	**0.92** ***	**0.90** ***	**0.89** ***	**0.22** ***	**0.35** ***	**0.25** ***	**0.20** ***	**0.16** ***	**0.15** ***	**0.16** ***
cohort1	0.07	0.11	0.11	0.09 **	0.06	0.06	-0.03	-0.10 ***	-0.26 ***	-0.24 ***	-0.20 ***	-0.11 ***	0.03	0.04
cohort2	0.10 ***	0.17 **	0.13 ***	0.13 ***	0.09 ***	0.07 **	-0.01	-0.08 ***	-0.16 ***	-0.15 ***	-0.11 ***	-0.09 ***	0.00	-0.01
cohort3	0.05 **	0.04	0.06 **	0.08 ***	0.06 ***	0.05 ***	0.00	0.02 *	-0.01	-0.01	0.00	0.03 *	0.05 ***	0.04
constant	1.58 ***	0.02	0.61 **	1.34 ***	2.00 ***	2.52 ***	3.24 ***	2.43 ***	1.80 ***	2.33 ***	2.63 ***	2.76 ***	2.64 ***	2.96 ***
Pseudo-R2	0.37	0.21	0.22	0.23	0.24	0.25	0.25	0.23	0.20	0.19	0.16	0.12	0.09	0.07

*Note: omitted variables are `no or primary education' and `cohort 4'. Stars report the level of significance (***:1%, **:5%, *:10%)*

Period 2

Coeff.	India							China						
	OLS	10%	20%	40%	60%	80%	90%	OLS	10%	20%	40%	60%	80%	90%
age	0.10 ***	0.15 ***	0.15 ***	0.13 ***	0.10 ***	0.06 ***	0.06 ***	0.21 ***	0.39 ***	0.27 ***	0.15 ***	0.10 ***	0.09 ***	0.11 ***
age2 /1000	-0.965 ***	-1.557 ***	-1.454 ***	-1.19 ***	-0.873 ***	-0.44 ***	-0.511 ***	-2.368 ***	-4.56 ***	-3.061 ***	-1.552 ***	-0.982 ***	-0.942 ***	-1.145 ***
female	-0.40 ***	-0.91 ***	-0.69 ***	-0.33 ***	-0.20 ***	-0.18 ***	-0.18 ***	-0.23 ***	-0.28 ***	-0.19 ***	-0.15 ***	-0.13 ***	-0.12 ***	-0.14 ***
mid-secondary	**0.27** ***	**0.30** ***	**0.26** ***	**0.27** ***	**0.21** ***	**0.21** ***	**0.17** ***	**0.29** ***	**0.52** ***	**0.42** ***	**0.27** ***	**0.19** ***	**0.16** ***	**0.08** **
higher secondary	**0.58** ***	**0.56** ***	**0.62** ***	**0.60** ***	**0.53** ***	**0.52** ***	**0.49** ***	**0.50** ***	**0.78** ***	**0.66** ***	**0.44** ***	**0.33** ***	**0.27** ***	**0.22** ***
college	**0.96** ***	**1.00** ***	**1.07** ***	**1.03** ***	**0.95** ***	**0.94** ***	**0.93** ***	**0.68** ***	**1.00** ***	**0.84** ***	**0.61** ***	**0.44** ***	**0.41** ***	**0.34** ***
cohort1	0.10	0.21	0.22 **	0.18 ***	0.09 **	0.00	0.06	0.55 ***	1.02 ***	0.69 ***	0.38 ***	0.20 ***	0.21 ***	0.34 ***
cohort2	0.10 **	0.14	0.18 ***	0.17 ***	0.08 **	0.02	0.05	0.28 ***	0.54 ***	0.40 ***	0.19 ***	0.05	0.15 ***	0.25 ***
cohort3	0.07 ***	0.08	0.12 ***	0.12 ***	0.07 ***	0.05 **	0.06 ***	0.09 ***	0.20 ***	0.16 ***	0.07 **	0.00	0.04	0.05
constant	1.49 ***	-0.12	0.12	0.87 ***	1.80 ***	2.86 ***	2.96 ***	-0.63 **	-5.02 ***	-2.42 ***	0.44 *	1.81 ***	2.14 ***	2.08 ***
Pseudo-R2	0.26	0.15	0.19	0.23	0.25	0.25	0.26	0.16	0.16	0.13	0.10	0.08	0.06	0.05

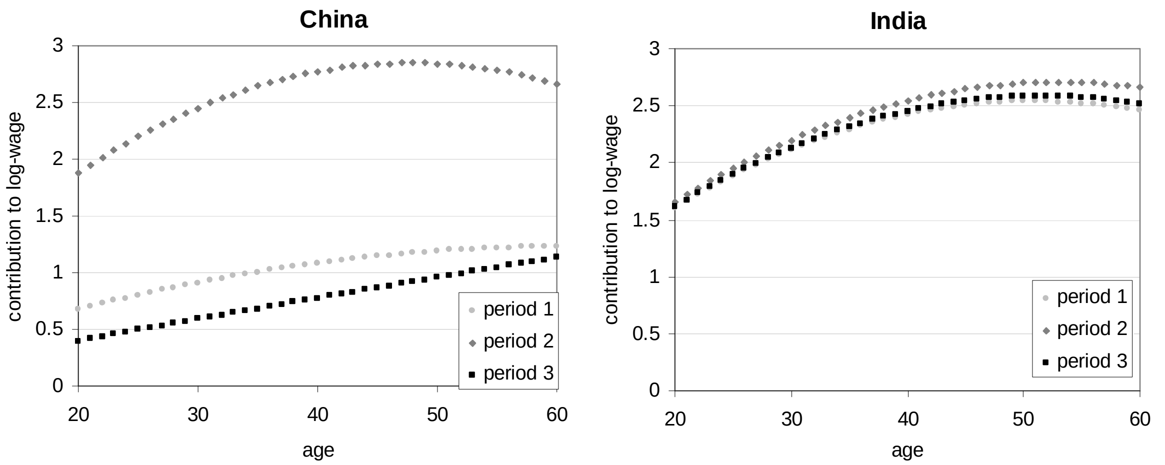
*Note: omitted variables are `no or primary education' and `cohort 4'. Stars report the level of significance (***:1%, **:5%, *:10%)*

Period 3

Coeff.	India							China						
	OLS	10%	20%	40%	60%	80%	90%	OLS	10%	20%	40%	60%	80%	90%
age	0.11 ***	0.14 ***	0.13 ***	0.11 ***	0.11 ***	0.08 ***	0.07 ***	0.05 ***	0.09 ***	0.07 ***	0.03 **	0.04 ***	0.04 **	0.04 *
age2 /1000	-0.962 ***	-1.373 ***	-1.209 ***	-0.92 ***	-0.908 ***	-0.565 ***	-0.552 ***	-0.374 ***	-0.952 ***	-0.586 ***	-0.187	-0.202	-0.298	-0.279
female	-0.41 ***	-0.75 ***	-0.65 ***	-0.49 ***	-0.28 ***	-0.16 ***	-0.16 ***	-0.14 ***	-0.21 ***	-0.19 ***	-0.15 ***	-0.12 ***	-0.11 ***	-0.13 ***
mid-secondary	**0.27** ***	**0.25** ***	**0.26** ***	**0.28** ***	**0.24** ***	**0.22** ***	**0.21** ***	**0.21** ***	**0.19** **	**0.22** ***	**0.20** ***	**0.28** ***	**0.18** ***	**0.08**
higher secondary	**0.60** ***	**0.55** ***	**0.55** ***	**0.60** ***	**0.57** ***	**0.57** ***	**0.56** ***	**0.46** ***	**0.39** ***	**0.47** ***	**0.46** ***	**0.52** ***	**0.41** ***	**0.32** ***
college	**1.14** ***	**1.04** ***	**1.15** ***	**1.16** ***	**1.12** ***	**1.08** ***	**1.08** ***	**0.76** ***	**0.77** ***	**0.84** ***	**0.77** ***	**0.78** ***	**0.67** ***	**0.60** ***
cohort1	0.15 *	0.20	0.26 *	0.15	0.17 **	-0.02	-0.04	-0.03	-0.02	-0.03	-0.08	-0.01	0.08	0.01
cohort2	0.08	0.11	0.09	0.07	0.10 *	-0.01	-0.02	0.08	0.02	0.04	0.02	0.12 *	0.13	0.20 *
cohort3	0.07 *	0.07	0.08	0.04	0.07 **	0.05	0.05	0.03	0.01	0.04	0.00	0.07 *	0.04	0.00
constant	1.40 ***	0.25	0.55	1.27 ***	1.54 ***	2.66 ***	3.02 ***	2.91 ***	1.42 **	2.13 ***	3.14 ***	3.19 ***	3.45 ***	3.88 ***
Pseudo-R2	0.42	0.20	0.22	0.26	0.28	0.27	0.26	0.17	0.10	0.11	0.11	0.10	0.08	0.08

*Note: omitted variables are `no or primary education' and `cohort 4'. Stars report the level of significance (***:1%, **:5%, *:10%)*

Figure 3: wage progression



The change in the age-earnings profile in China, which led to a more pronounced inverted-U shape of the profile in period 2 compared to that in period 1, was also observed by Knight and Song (2003). The sharp decline in the returns to age/experience in China in period 3 is possibly a consequence of the structural reforms in China that were initiated in the mid-1990s. As part of the structural reforms, wages were decontrolled significantly, and became, at least in part, market determined. At the same time, the government initiated a reform of the public sector enterprises, paving the way for redundancies, largely among the older sections of the work force. The sharp reduction of the returns to age in China between periods 2 and 3 is possibly a manifestation of the loss of wage bargaining power of the labour force in general, and among the older sections of the labour force in particular.

The estimates of returns to education indicate the following. First, the returns increase consistently with the education level, for both countries, at all times and for all quantiles. Second, with a few exceptions, the marginal impact of all education levels on earnings is lower for lower earnings quantiles than for higher earnings quantiles. This is especially true for China. Third, there were clear differences in the evolution of returns to education in China and India over time. In period 1, returns to education were higher in India than in China, particularly for higher secondary and college education. Returns to education rose rapidly in China between periods 1 and 2, catching up with, and in some cases, exceeding those in India in the latter period. In period 3, returns to college education rose significantly in India, across earnings quantiles, while returns to other levels of education either remained the same or increased marginally. In China, on the other hand, there was a clear division. Returns to education rose, by and large, for all education levels for the upper earnings quantiles. At the same time, however, there was noticeable decline in returns to education among workers in the lower earnings quantiles.

While estimates are plausible and qualitatively consistent with the overall literature, they explain inter-personal variations in earnings much better for the Indian than for the Chinese labourers, as reflected by the lower pseudo R-square for China at all periods. In other words, the human capital theory which form the basis for the Mincer equation is more applicable in India than in China, even as late as 2002 and despite improvement in the competitiveness of the Chinese labour market.[11]

4. Decomposing wage differential between China and India

Earlier in this paper, we observed that the growth rate of mean (and median) earnings in China was much higher than the corresponding growth rate in India. We also observed a much more rapid increase in returns to education in China than in India, especially for the upper earnings quantiles. In order to better understand the extent to which these two phenomena are relared, we decompose the difference in average (log) earnings between formal sector employees in India and China into *endowment effect* which manifests the impact of the difference in the average characteristics of the Chinese and Indian workers on the differences in their earnings, and *coefficients effect* which captures the impact of the differences in the returns on these endowments (including returns to education) on the Indo-Chinese difference in earnings. Following the approach initiated by Blinder (1973) and Oaxaca (1973), we have

$$Ln\overline{Y}_I - \ln\overline{Y}_C \equiv \overline{X}_C'(\hat{\beta}_I - \hat{\beta}_C) + (\overline{X}_I - \overline{X}_C)'\hat{\beta}_I \qquad (2)$$

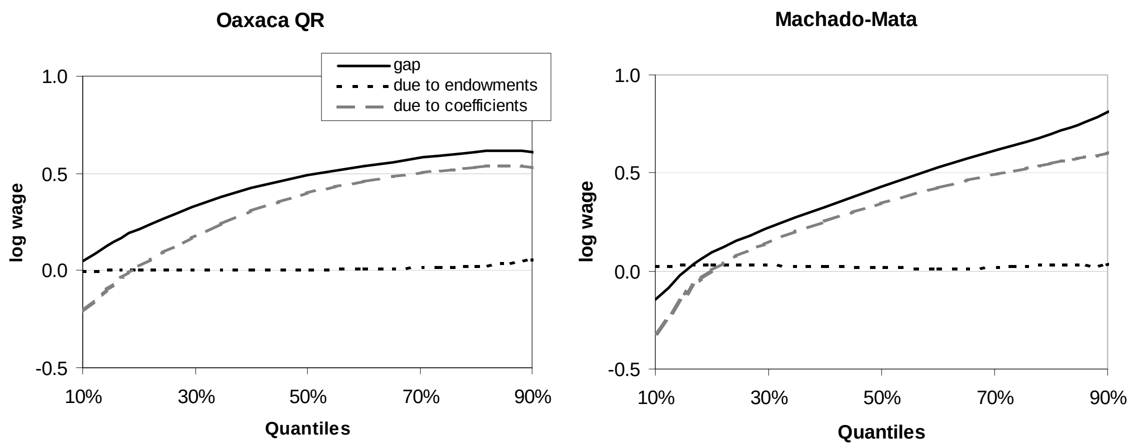
where subscripts *I* and *C* refer to India and China respectively, while vectors β and X refer to the estimated coefficients and the covariates (or worker endowments) specified in equation (1). The first term on the right hand side of the identity is the coefficients effect and the second term is the endowments effect.

[11] For a discussion about the evolution and the increasing competitiveness of the Chinese labour market, see Song and Knight (2005).

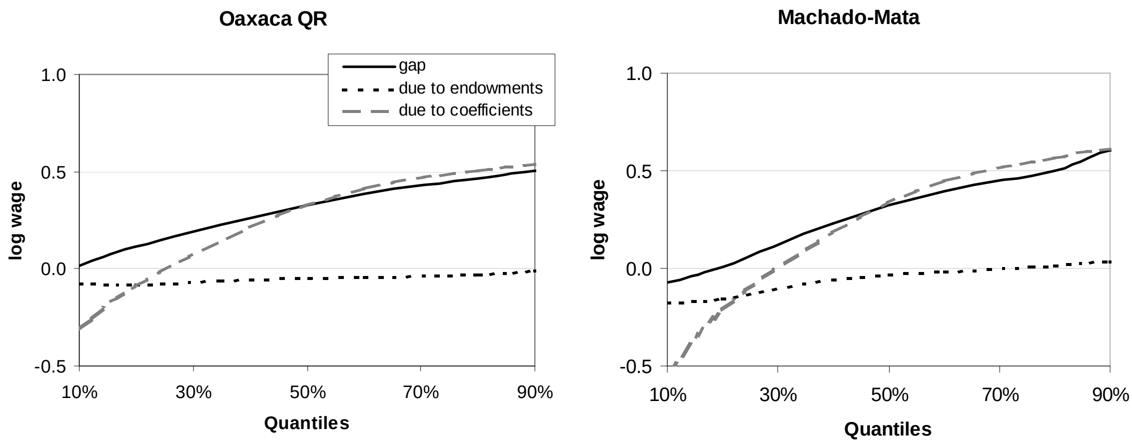
In order to decompose the difference in (log) earnings across the distribution, we refine the above algorithm in two ways. First, instead of using the OLS estimates that are estimated at the mean of the distribution, we use the coefficient estimates generated by the quantile regression models, even as we use the mean value of the worker characteristics. We call this the *Oaxaca-quantile regression* (or Oaxaca QR) method. Next, we use the Machado-Mata (2005) algorithm that decomposes the difference in (log) earnings in China and India at the n^{th} percentile of the distribution using coefficient estimates as well as values of the X vectors for the two countries at those percentiles. As demonstrated by Autor et al. (2005), the Machado-Mata approach nests most of the usual approaches. The method combines quantile regression and bootstrapping to generate two counterfactual density functions: (i) the Chinese log wage density function that would arise if Chinese workers had the same characteristics or endowments as their Indian counterparts, but continued to experience the same returns to these endowments (as in China), and (ii) the density function that would arise if the Chinese workers retained their own characteristics but had the same returns to these characteristics as the Indian workers. A description of the technique and an analysis of its asymptotic properties are provided by Albrecht et al. (2006).

Figure 4: Oaxaca QR and Machado-Mata decompositions

Period 1



Period 2



Period 3

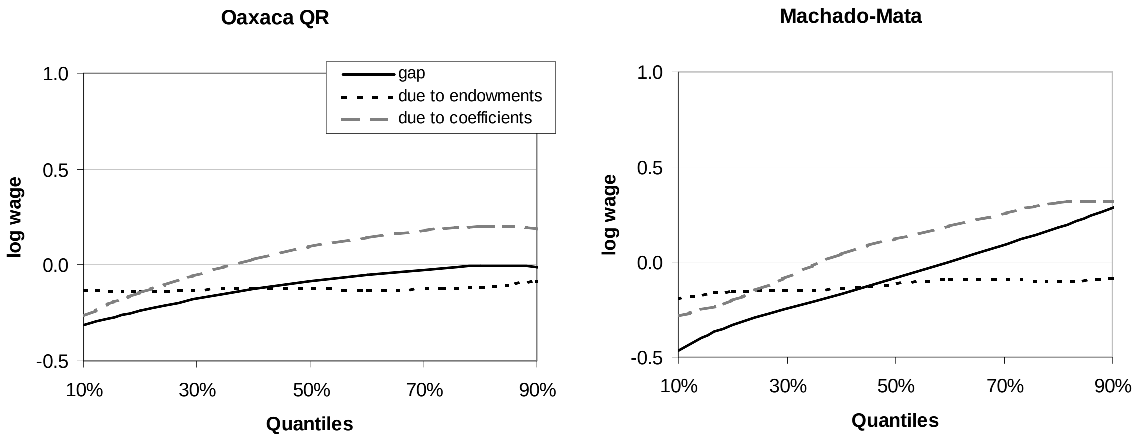


Figure 4 reports the result of the decomposition for all three periods, using both Oaxaca QR and Machado-Mata techniques. The results generated by the two algorithms highlight very similar patterns, indicating that our decomposition results are robust. To recapitulate, average earnings for Indian wage earners were much higher than those of the Chinese wage earners for all earnings quantiles. By period 2, the Indo-Chinese gap in earnings was reduced significantly. Finally, by period 3, earnings of Chinese wage earners were higher for lower earnings quantiles, and the Indian advantage further reduced for the upper earnings quantiles. The graphs reported in Figure 4 indicate that the coefficients effect explains most of the log-wage gap between the two countries, at least for the two first periods. The endowments effect is consistently negative for all periods and for all earnings quantiles, perhaps manifesting the Chinese advantage in terms of educational attainment. However, this advantage is more than offset for the middle and upper earnings quantiles by the much higher returns to worker characteristics (particularly, age and education) in India. The Indian advantage with respect to returns to education can be seen in Table 3.

Table 3: India-China differential in returns to education

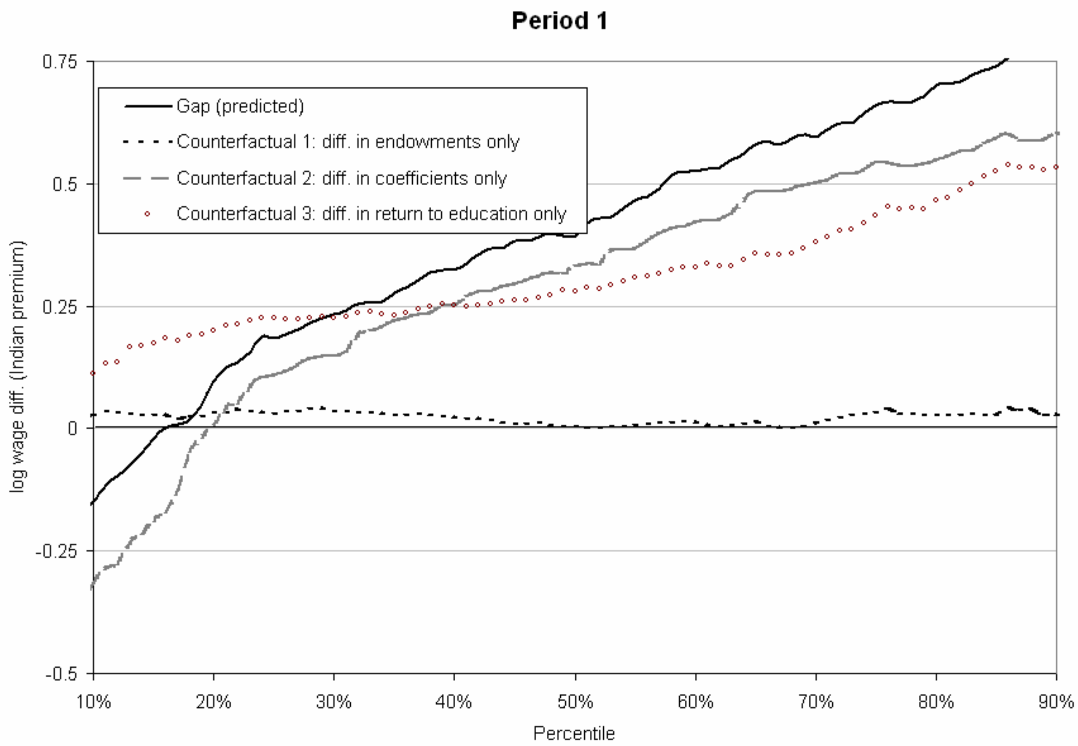
	period	10%	20%	40%	60%	80%	90%
Oaxaca QR coefficient effect							
	1	0.24	0.32	0.31	0.32	0.29	0.33
	2	-0.15	-0.01	0.16	0.21	0.24	0.28
	3	0.17	0.15	0.22	0.14	0.22	0.30
Machado-Mata counterfactual							
	1	0.11	0.20	0.25	0.33	0.47	0.53
	2	-0.25	-0.08	0.06	0.17	0.35	0.37
	3	0.08	0.12	0.12	0.16	0.26	0.31

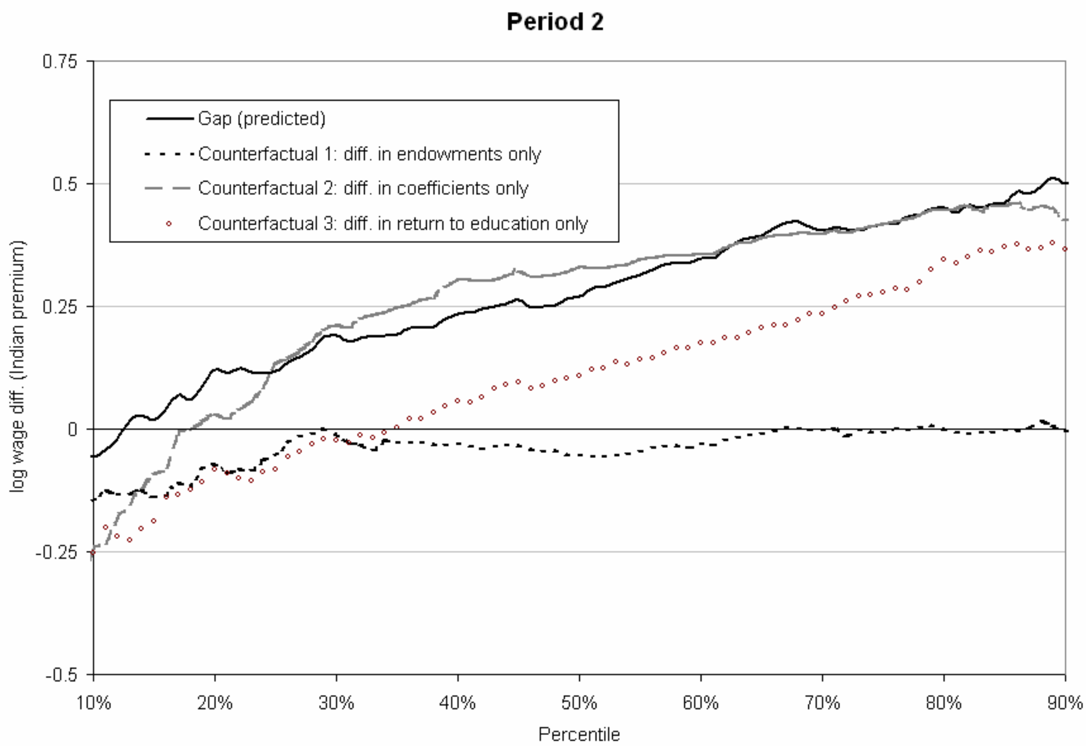
For both techniques, figures represent the Indian–Chinese gap in log-wage which is explained by differences in returns to education

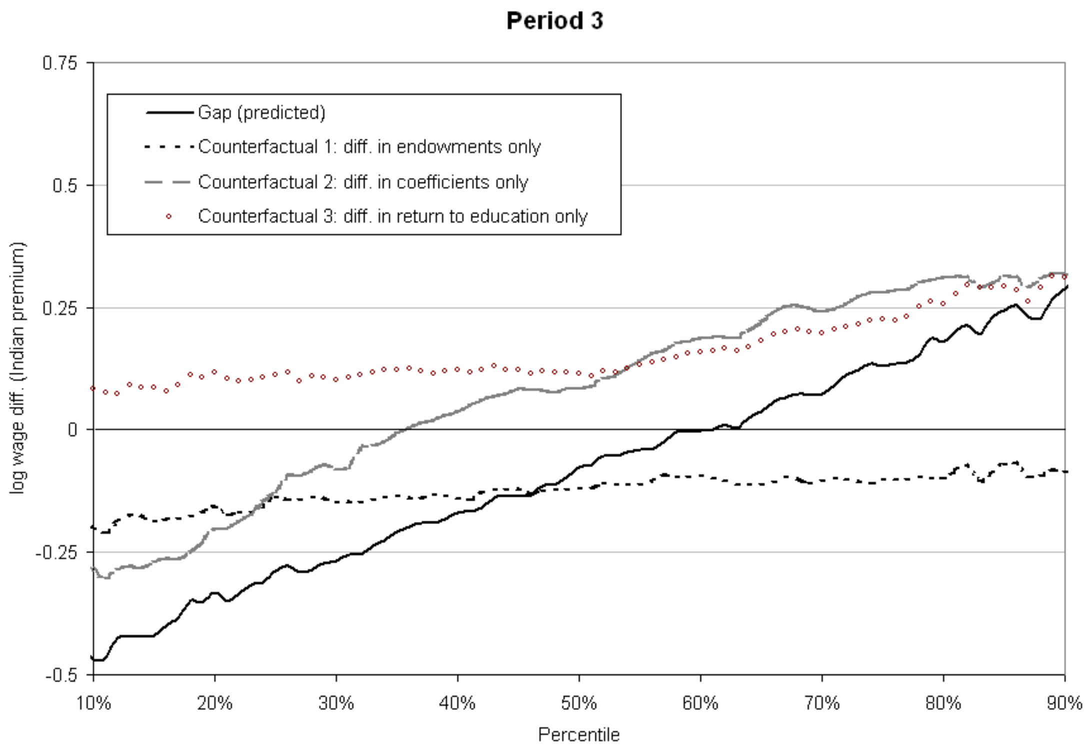
We examine the role of differences in returns to education in explaining Indo-Chinese differences in (log) earnings further using the counterfactuals for returns to education generated by the Machado-Mata algorithm. The counterfactual estimates the impact of the differences in returns to education on the earnings differential under the assumption that the average characteristics of the Indian and Chinese wage earners, as well as the returns on all other characteristics, are equal. The results are reported in Figure 5.

The graphs suggest that the differences in returns to education explain a significant proportion of the differences in (log) earnings in all three periods. Further, in periods 1 and 2, the counterfactual for returns to education over-predicts the differences in (log) earnings for the lower earnings quantiles, and under-predicts it for the upper earnings quantiles. This is consistent with the earlier observation that the Indo-Chinese differences in returns to education are higher for upper earnings quantiles than for lower earnings quantiles. In period 3, this counterfactual over-predicts the earnings gap for all earnings quantiles, especially for the lower end of the distribution. In other words, earnings gap in period 3, which witnessed a decline in the advantage of the Indian wage earners, would have been higher, and in favour of the Indians, if the gap were determined by differences in returns to education alone. Once again, this is consistent with the higher estimated returns to education for India than for China.

Figure 5: Machado-Mata decomposition and differences in returns to education


Period 1
Gap (predicted)
Counterfactual 1: diff. in endowments only
Counterfactual 2: diff. in coefficients only
Counterfactual 3: diff. in return to education only
log wage diff. (Indian premium)
0.75
0.5
0.25
0
-0.25
-0.5
10%
20%
30%
40%
50%
60%
70%
80%
90%
Percentile


Period 2
Gap (predicted)
Counterfactual 1: diff. in endowments only
Counterfactual 2: diff. in coefficients only
Counterfactual 3: diff. in return to education only
log wage diff. (Indian premium)
0.75
0.5
0.25
0
-0.25
-0.5
10%
20%
30%
40%
50%
60%
70%
80%
90%
Percentile



In sum, it is difficult to satisfactorily explain the much faster rate of growth in mean (and median) earnings of the Chinese workers on the basis of differences in returns on earnings. Ceteris paribus, and with one exception (bottom 30% of wage earners in period 2), the latter difference would have led to a sustained Indian advantage in all three periods, even though the advantage was declining over time. Even after this decline in the Indian advantage is taken into account, the much faster growth in average Chinese earnings would have to be explained largely by other factors such as the rapid improvement in the average education levels of the Chinese wage earners over time. (Note that greater female participation in the labour force goes *against* China on account of the fact that females earn less than men, and hence greater female participation reduces the average earnings of the labour force.)

5. Concluding remarks

Despite the simultaneous rise of China and India as major economic powers, there are few rigorous comparative studies of the two countries. In particular, while researchers have individually examined returns to education in the two countries, given the importance of human capital in determining the competitive edge and growth paths of these economies in the future, there is no comparative study of returns to education of these two countries using comparable data and a common framework. In this paper, we have addressed this lacuna in the literature. Our results indicate that the gap in average earnings, which was in favour of the Indian wage earners in the late-1980s, declined rapidly over time, especially for the people in the upper earnings quantiles. However, this shift cannot be satisfactorily explained in terms of differences in returns to education. While returns to education rose significantly in China, especially between periods 1 and 2, the returns in India continued to be higher in all three periods. The main driver of the rising average earnings of the Chinese wage earners was the rapid rise in the average education level of the Chinese work force.

Our results brings to fore a paradox, namely, that even as returns to education are higher in India, improvement in educational attainment has taken place much faster in China. As explained earlier in this paper, it is difficult to explain this in terms of differences in public expenditure on education in the two countries. The explanation has to lie in slower growth of demand for education in India. This, indeed, is the crux of the paradox; higher returns to education should, in principle, be related to higher demand for education, which is clearly not the case. This raises questions about the extent to which returns to education in India are uncertain, and the nature of barriers that may be preventing a transformation of latent demand for education into actual demand. At the very least, this calls for a careful analysis of education policy in India, and an identification of the lessons that can be learnt from China's greater success with imparting education to its labour force.

References

Albrecht, J., A. Bjorklund and S.C. Vroman, S. (2003) Is there a glass ceiling in Sweden? *Journal of Labor Economics*, **21**, 145-77.

Albrecht, J., A. van Vuuren and S.C. Vroman (2006) Counterfactual distribution with sample selection adjustments: econometric theory and an application to the Netherlands. Mimeo, Georgetown University, Washington, D.C.

Altonji, J.G. (1993) The Demand for and Return to Education when Education Outcomes are Uncertain. *Journal of Labor Economics*, **11**:1, 48-83.

Autor, D, L. Katz and M. Kearney (2005) Rising wage inequality: the role of composition and prices, Working paper no. 11628, National Bureau of Economic Research, Cambridge, Massachusetts.

Banga, R. (2006) Critical issues in India's service-led growth. INRM policy brief no. 2, Asian Development Bank, New Delhi.

Banerjee, A.V. and T. Picketty (2005) Top Indian Incomes, 1922-2000. *World Bank Economic Review*, **19**:1, 1-20.

Bardhan, P. (2006) Crouching Tiger, Lumbering Elephant: A China-India Comparison, University of California at Berkeley

Bhaumik, S., and M. Chakrabarty (2007) Is Education the Panacea for Economic Deprivation of Muslims? Evidence from Wage Earners in India, 1987-2004. Working paper no. 858, William Davidson Institute, University of Michigan, Ann Arbor.

Blinder, A. S. (1973) Wage discrimination: Reduced form and structural variables. *Journal of Human Resources*, **8**, 436-455.

Borooah, V., B., Gustafsson and L. Shi (2006) China and India: Income Inequality and Poverty North and South of the Himalayas. *Journal of Asian Economics*, **17**:5, 797-817

Bray, M. (2002) The costs and financing of education: Trends and policy implication. Asian Development Bank, Manila.

Cai, F. (2005) Reform of labor policy in China: A perspective of political economy. In *CHINA: An Economics Research Study Series – Volume 4: Reforming China*, edited by the Institute of World Economics and Politics, Chinese Academy of Social Sciences. Singapore: Marshall Cavendish Academic.

Card, D. (1999) The causal effect of education on earnings. In: Orley Ashenfelter and David Card (Eds.) *Handbook of Labour Economics*, **3**:1, 1801-1863.

Carnoy, M. (2006): Higher education and economic development: India, China and the 21st century, paper presented at the *Pan Asia Conference: Focus on Economic Challenges*, Stanford Center for International Development, May 31- June 3, 2006

Demurger, S., M. Fournier, L. Shi and W. Zhong (2006) Economic liberalisation with rising segmentation on China's urban labour market. Working paper no. WP 2006-46, ECINEQ – Society for the Study of Economic Inequality, Spain.

Dev, S. Mahendra (2002) Pro-poor growth in India: What do we know about the employment effects of growth 1980-2000. Working paper no. 161, Overseas Development Institute, London.

Duraisamy, P. (2002) Changes in returns to education in India, 1983-94: By gender, age-cohort and location. *Economics of Education Review*, 21:6, 609-22.

Fan C. S and X. Wei (2006) The Law of One Price: Evidence from the Transitional Economy of China. *Review of Economics and Statistics*, **88**:4, 682-697.

Fields, G. (2005) A Guide to Multisector Labor Market Models, World Bank working paper.

Gajwani, K., R. Kanbur and X. Zhang (2006) Patterns of Spatial Convergence and Divergence in India and China, Paper prepared for the Annual Bank Conference on Development Economics (ABCDE), St. Petersburg, January 18-19, 2006.

Kijima, Y. (2006) Why did wage inequality increase? Evidence from urban India 1983-99. *Journal of Development Economics*, **81**:1, 97-117.

King, E.M. et al. (2000) Engender development though gender equality in rights, resources and voice. Policy research report no. 21412, The World Bank, Washington, D.C.

Knight, J. and L. Song (2003) Increasing urban wage inequality in China. *Economics of Transition*, **11**:4, 597-619.

Koenker, R. and G. Bassett (1978) Regression Quantiles, *Econometrica*, 46:33-50

Lemieux, T. (2006): The Mincer equation thirty years after Schooling, Experience and Earnings. In: S. Grossbard-Shechtman (Ed.) *Jacob Mincer: A Pioneer of Modern Labour Economics*, Springer Verlag.

Lewis, W. A. (1954) Economic development with unlimited supplies of labour. *Manchester School*, **22**, 139-191.

Machado, J. and J. Mata (2005) Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics*, **20**:4, 445-465.

Melly, B. (2005) Public-private sector wage differentials in Germany: evidence from quantile regression, *Empirical Economics*, 30(2), 505-520.

Meng, X. (2004) Economic Restructuring and Income Inequality in Urban China. *Review of Income and Wealth*, ….

Mueller, Richard (1998) Public-private sector wage differentials in Canada: evidence from quantile regressions. *Economics Letters*, **60**, 229-235.

Munshi, K. and M. Rosenzweig (2003) Traditional institutions meet the modern world: Caste, gender and schooling choice in a globalizing economy. Working paper no. 038, Bureau of Research and Economic Analysis of Development, Cambridge, Massachusetts.

National Bureau of Statistics of China (2005), China Statistical Yearbook 2005, Beijing: China Statistics Press.

Oaxaca, R. (1973) Male-female wage differentials in urban labor markets. *International Economic Review* **14**, 693-709.

Psacharopoulos, G. (1985) Returns to education: A further international update and implications. *Journal of Human Resources*, **20**:4, 583-604.

Psacharopoulos, G. and H. A. Patrinos (2004) Returns to investment in education: A further update. *Education Economics*, **12**:2, 111-134.

Piketty, T. and N. Qian (2004) Income Inequality and Progressive Income Taxation in China and India, 1986-2010, MIT working paper.

Rajan, R. and Arvind S. (2006) India needs skills to solve the “Bangalore bug”. *Financial Times*, March 17, http://www.imf.org/external/np/vc/2006/031706.htm.

Saha, B. and S. Sarkar (1999) Schooling, informal experience, and formal sector earnings: A study of Indian workers. *Review of Development Economics*, **3**(2): 187-199.

Song, L. and J. Knight (2005) *Towards a Labour Market in China*. Oxford: Oxford University Press.

Subramanian, S. (1973) Economic Growth in China and India, 1952-1970: A Comparative Appraisal. *Economic Development and Cultural Change*, **21**:4, 1-84

Yang, T. (2005) Determinants of schooling returns during transition: Evidence from Chinese cities. *Journal of Comparative Economics*, **33**:2, 244-264.