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EARNINGS DIFFERENCES BETWEEN CHINESE AND INDIAN WAGE EARNERS, 1987–2004

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This paper is one of the first comprehensive attempts to compare earnings in urban China and India over the recent period. While both economies have grown considerably, we illustrate significant cross-country differences in wage growth since the late 1980s. For this purpose, we make use of comparable datasets, estimate Mincer equations and perform Oaxaca–Blinder decompositions at the mean and at different points of the wage distribution. The initial wage differential in favor of Indian workers, observed in the middle and upper part of the distribution, partly disappears over time. While the 1980s Indian premium is mainly due to higher returns to education and experience, a combination of price and endowment effects explains why Chinese wages have caught up, especially since the mid-1990s. The price effect is only partly explained by the observed convergence in returns to education; the endowment effect is driven by faster increase in education levels in China and significantly accentuates the reversal of the wage gap in favor of this country for the first half of the wage distribution.

1. INTRODUCTION

A growing literature compares average earnings or wage distributions across countries and investigates how standard human capital factors can explain these wage differentials, relying in particular on the well-known Oaxaca–Blinder decomposition or some of its extensions. For instance, Blau and Khan (1996) compare the distributions of male wages across ten industrial countries and study to which extent differences are explained by returns to education. Bourguignon *et al.* (2007) extend the Oaxaca–Blinder technique to decompose differences in household

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income distributions, and therefore household inequality measures, between the U.S. and Brazil. Almeida dos Reis and Paes de Barros (1991) study changing wage distributions across regions in Brazil. Donald *et al.* (2000) simulate counterfactual density functions to decompose differences in wage distributions between the U.S. and Canada.

By contrast, despite the continual comparisons of the Chinese and Indian growth stories, no systematic attempt has been made to compare wage distributions in India and China and their determinants.[1] There are however many motivations to do so. Firstly, with respectively 1.3 and 1.1 billion inhabitants, these countries represent the largest pool of workers in the world; the evolution of wages in these countries is therefore a determinant aspect of past and future changes in world inequalities and in global poverty levels. Political stability within these countries also depends to some extent on the way inequalities will develop in the future. Secondly, after an outstanding phase of economic expansion (50 percent in real terms over the 1990s), these two countries face a similar challenge to perpetuate high growth rates in the future. This challenge pertains in particular to their ability to sustain the supply of skilled and semi-skilled laborers to rapidly growing industries and, therefore, on political choices regarding education policies. Understanding how past policies have actually affected skills, and hence wage levels, is an important step. Finally, both countries have experienced profound reforms of their economy and their labor market; it is therefore important to assess how wage profiles have evolved over time in response to these policies and in particular to changes in pay policies and returns to experience.

While this paper does not have the ambition to cover all these questions, it suggests nonetheless one of the first systematic comparisons of wage profiles between China and India. Precisely, we focus on urban sectors in both countries and provide a comprehensive description of Indo-Chinese wage differentials and their determinants since the late 1980s. We address the cross-country comparison by gathering earnings data with comparable variable definitions across countries and for comparable periods. We also make use of the standard Mincer equation to perform Oaxaca–Blinder decompositions of the mean wage difference as well as recently developed quantile decompositions. This way, we examine the extent to which Indo-Chinese wage differences can be explained by differences in workers' characteristics (experience, education, etc) and returns to these characteristics, both on average and for the whole wage distribution.[2]

We find that the initial wage differential in favor of Indian workers, observed in the middle and upper part of the distribution, partly disappears over time. While the 1980s Indian premium is mainly due to higher returns to education and

[1]However, wage determinants have been separately analyzed for each country, including numerous estimations of returns to education for various time periods; see Byron and Manaloto (1990), Liu (1998), Knight and Song (2003), Zhang *et al.* (2005) and Appleton *et al.* (2005) for China, and Saha and Sarkar (1999), Kingdon and Unni (2001), Duraisamy (2002) and Kijima (2006) for India.

[2]Note that we do not address the question of income inequality since this would require considering household income rather than individual wages. The extension of the decomposition approach to household income distributions involves at least two additional dimensions (other than observed characteristics and returns to these characteristics), namely occupational status of household members and household composition. Bourguignon *et al.* (2007) suggest one of the first regression-based approaches in this direction.

experience, a combination of price and endowment effects explains why Chinese wages have caught up, especially since the mid-1990s. The price effect is only partly explained by the observed convergence in returns to education; the endowment effect is driven by faster increase in education levels in China and significantly accentuates the reversal of the wage gap in favor of this country for the first half of the wage distribution.

The rest of the paper is structured as follows. In Section 2, we report the nature of the data, the associated descriptive statistics and basic comparisons of wage distributions. Earnings estimations, and returns to education and to experience in particular, are presented and discussed briefly in Section 3. Sections 4 and 5 report the results of the decomposition analysis, respectively at the mean and for the entire distribution. Section 6 concludes.

2. Data Description and Wage Differential

Our empirical exercise is based on earnings data for regular wage earners in India and China. 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 organized by the Central Statistical Organisation, and they 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 Employment and Unemployment Schedule of the NSS is the only source of information for earnings and worker characteristics in India. It is stylized to exclude from the sample self-employed and casual workers, such that the sample only includes wage earners who work full time and do not attend school. In addition, possibly to minimize measurement error, it is customary to restrict the sample to urban workers who account for 85 percent of all wage earners in the sample (see Kijima, 2006).

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 11 provinces in China and resembling the actual distribution of populations across these regions (see Demurger *et al.*, 2006).[4] In order to make the Chinese sample comparable with the Indian sample, we restrict the former to urban wage earners working full time, thereby making the sample similar to the one used by Liu (1998), Knight and Song (2003) and Zhang *et al.* (2005).

Both surveys provide information on earnings, age, education and gender of labor force participants, plus industry types and country-specific variables. We

[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.

[4]Provinces are Beijing, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Guangdong, Sichuan, Yunnan and Gansu. The 1988 data covers 10 provinces. In 1995, Sichuan province was added in the survey. In 2000, Chongqing was separated from Sichuan and became a provincial-level city itself but is here treated as part of Sichuan. Note that Zhang *et al.* (2005) use data on Beijing, Shanxi, Liaoning, Zhejiang, Guangdong, Sichuan, and argue that these six provinces are broadly representative of China's rich regional variation.

further restrict both samples to 21–60 year olds. The Chinese weekly earnings is taken directly from survey in 1988 while it is calculated from yearly earnings in 1995 and 2002. The Indian NNS reports weekly earnings. In order to make the earnings data comparable across countries and years, we transform all (weekly) wages into 2000 PPP USD equivalent using the World Development Indicators (WDI) on consumer price indices and PPP conversion factors.

The issue about PPP adjustments is a sensitive one and deserves some discussion. The main source of information is the Penn World Table (PWT), which provides measures of real GDP per capita at constant international prices. It is based on detailed price surveys gathered by over one hundred countries since 1950 under the auspices of the International Comparison Program (ICP). Several methods have been suggested to construct aggregated PPP indices, but two methods are mainly in use: the Geary–Khamis (GK) method, underlying the PWT and the WDI of the World Bank, and the Girardi and Elteto–Köves–Szulc (EKS) approach, used by Eurostat and the OECD since 1990.[5] Since PPP calculations can be sensitive to the methodology, we would ideally use alternative PPP estimates to verify the robustness of our results.[6] We simply report alternative figures from recent studies and show that the corrections affecting PPP factors for China and India are of the same order of magnitude. Firstly, it is noteworthy that ICP prior to 2005 did not include China and India.[7] Ackland *et al.* (2007) suggest a way to construct the GK and EKS income measures for these two countries based on the PWT 1996 estimates of real GDP per capita (derived by extrapolation from the ICP sample). Their imputed EKS (resp. GK) estimates are \$2,848 (resp. \$3,230) and \$2,023 (resp. \$2,308) for China and India respectively while the PWT 1996 measures are \$2,969 and \$2,118. Importantly for us, the difference between the two countries is similar according to the three methods (a ratio of 1.408 with EKS, 1.399 with GK and 1.402 with the PWT measures). Secondly, preliminary results of the most recent ICP (2005) have been recently published and include for the first time some estimates for China and India.[8] The GDPs per capita were substantially revised downward, compared to the 2005 WDI based on old extrapolations; yet, the revisions go in the same direction and are of similar magnitude for the two countries, namely −39.9 percent and −38.8 percent for China and India respectively. Overall, then, adjusted wage levels reported in the present study may not

[5]There is a considerable literature on the merits of these two and other methods. Briefly speaking, GK uses a fixed hypothetical world price structure which typically leads to a so-called substitution bias. The EKS method avoids this problem but gives all countries the same weight and also results in real expenditure calculations that are not additive. In the context of analyzing global poverty, Ackland *et al.* (2007) show that the EKS approach yields more appropriate international comparison of real incomes.

[6]Hill (2000) compares the range of estimates of PPP adjusted average income levels that 13 available methodologies imply, noting that calculated average income ratios can nearly double, depending on the chosen method.

[7]Estimates of Chinese PPP exchange rates were extrapolated from a bilateral comparison of 1986 prices between China and the U.S. Estimates for India were based on extrapolations of the 1985 results of the ICP. Dowrick and Akmal (2005) and Pogge and Reddy (2003), among others, offer a critical discussion about these estimates and the way they may impede international comparisons and global measures of poverty and inequality.

[8]*2005 International Comparison Program*: Preliminary Results, December 17, 2007. Available at www.worldbank.org/data/icp. Milanovic (2007) provides an enlightening discussion about the new improvements and the consequences on measures of world inequality.

compare accurately with the rest of the world but, most importantly, compare reasonably well between the two countries.

Finally, we harmonize education variables. While the NSS/Indian survey and 1988 wave of the CHIP/Chinese data include information on the levels of education alone, the 1995 and 2002 waves of CHIP data include both schooling years and education levels. Then, we construct four education categories—no education or primary education, middle secondary education, high secondary education, and college education—that are relatively comparable across countries and periods. The comparability issue is discussed in the Appendices, where we briefly describe the Indian and Chinese education system and the construction of the education (categorical) variables.

Descriptive statistics for the CHIP/Chinese data and the NSS/Indian data are reported in Tables 1a and 1b, for men and women respectively. Hereafter, period 1 refers to year 1987 for India and 1988 for China, period 2 to 1993 and 1995 respectively, and period 3 to 2004 and 2002. This is not a perfect time comparison but the best that could be done with available data.[9] Tables 1a and 1b indicate that in all three periods, Chinese wage earners in our sample are older on average than their Indian counterparts, and hence have larger potential experience. Women constitute a significantly greater proportion of the wage earning workforce in China—around half of the workers—than in India, perhaps reflecting higher educational attainment of an average Chinese woman;[10] or the socialist ideology that promotes equal employment opportunity for men and women.

While India had more college educated workers in the late 1980s, especially among women (9 percent in China versus 32 percent in India), the situation has changed rapidly since the 1990s.[11] By 2002–04, however, the picture had changed remarkably, with 39 percent of Chinese male wage earners achieving a college degree versus 29 percent in India, and a partial catching up for women (34 percent in China versus 42 percent in India). Moreover, while almost all of the Chinese workers had at least middle secondary education in the last period, 29 percent of women and 19 percent of men still had only primary or no education in India. The rapid skill increase in China is in line with the significant shift in the structure of this economy in the late 1990s—with high technology industries and services progressively accounting for greater share of value added and employment—and

[9]Note that sample sizes are much smaller in the last period. For Chinese data, this is mainly due to financial reasons. Nevertheless, the three waves cover the same provinces (with the exception of Sichuan, not in the 1988 sample). For India, we use the large quinquennial survey of NSS for periods 1987 and 1993/4. For the Indian data to be close in time to the Chinese 2002 sample—the next quinquennial survey came to release only recently—we have used the smaller round of NSS data for 2004. This data is a separate employment–unemployment survey mimicking the structure of bigger rounds and comparable to those. That is, sample sizes should only affect standard error but not estimates. Note that the China Health and Nutrition Survey would allow a better match but sample sizes were simply too small.

[10]Female literacy rate in China was 86 percent in 2002, compared to 48 percent in India in 2003.

[11]This is in line with the fact that growth in India has relied significantly on expansion of the skill-intensive service sector (in particular business services, communication services and banking) and also skill-based manufacturing industries (like auto ancillaries and pharmaceuticals). This is in contrast with the growth path in China, and notably that of the manufacturing sector which was primarily labor-intensive and did absorb surplus agricultural labor.

TABLE 1a
Descriptive Statistics (Men)

Period	India 1	India 2	India 3	China 1	China 2	China 3
No. of observations	19,116	18,226	8,183	8,665	6,089	4,609
Age	37.3	37.8	37.5	39.4	40.5	42.2
Education (years)	9.0	9.4	10.1	9.6	11.1	11.7
Education (categories)						
No or primary education	0.33	0.25	0.19	0.11	0.05	0.02
Middle secondary education	0.15	0.16	0.19	0.36	0.28	0.22
High secondary education	0.29	0.31	0.34	0.35	0.38	0.36
College	0.23	0.28	0.29	0.18	0.29	0.39
Industry						
Manufacturing	0.28	0.28	0.25	0.45	0.45	0.32
Construction and utilities*	0.16	0.16	0.18	0.09	0.06	0.14
Wholesale & retail trade	0.06	0.07	0.13	0.11	0.11	0.06
Finance, insurance, real estate	0.06	0.05	0.05	0.02	0.02	0.04
Services	0.15	0.17	0.19	0.15	0.15	0.21
Public administration	0.25	0.23	0.17	0.12	0.14	0.16
Others**	0.03	0.04	0.03	0.06	0.03	0.05
Weekly wage	92	107	144	57	77	144

Notes: Period 1 is 1987 for India (1988 for China); period 2 is 1993/94 (1995); period 3 is 2004 (2002). Selection: urban workers in formal sector, aged 21–60. Weekly wages are expressed in 2000 PPP international USD.

*Transportation, communications, electricity, gas, sanitary services, water supply.

**Agricultural, forestry, fishing, mining.

TABLE 1b
Descriptive Statistics (Women)

Period	India 1	India 2	India 3	China 1	China 2	China 3
No. of observations	3,340	3,435	1,742	7,803	5,597	3,564
Age	36.7	37.0	36.9	36.4	38.4	39.2
Education (years)	8.7	9.3	9.9	9.0	10.4	11.6
Education (categories)						
No or primary education	0.37	0.30	0.29	0.15	0.07	0.02
Middle secondary education	0.05	0.05	0.08	0.40	0.33	0.19
High secondary education	0.26	0.27	0.21	0.37	0.42	0.45
College	0.32	0.38	0.42	0.09	0.18	0.34
Industry						
Manufacturing	0.13	0.12	0.11	0.48	0.42	0.28
Construction and utilities*	0.04	0.04	0.06	0.05	0.04	0.09
Wholesale & retail trade	0.01	0.02	0.04	0.17	0.16	0.10
Finance, insurance, real estate	0.05	0.05	0.04	0.02	0.02	0.04
Services	0.56	0.55	0.63	0.18	0.20	0.32
Public administration	0.17	0.20	0.11	0.05	0.09	0.12
Others**	0.03	0.02	0.01	0.04	0.02	0.03
Weekly wage	71	88	116	47	63	120
Proportion of female in the sample	15%	16%	18%	47%	48%	44%

Notes: period 1 is 1987 for India (1988 for China); period 2 is 1993/94 (1995); period 3 is 2004 (2002). Selection: urban workers in formal sector, aged 21–60. Weekly wages are expressed in 2000 PPP international USD.

*Transportation, communications, electricity, gas, sanitary services, water supply.

**Agricultural, forestry, fishing, mining.

is also driven by strong political impulses.[12] As we shall see, higher educational endowment in China in the recent period has influenced significantly the wage differential across the two countries.

Tables 1a and 1b also report industry types, which are made comparable across countries. Manufacturing remains the largest sector in terms of male labor force in both countries, with a declining share over time. As expected, it represents a larger proportion of the labor force in China and also employs a large share of women in this country. Services are the main employer for women in both countries, with a very large share in India and an increasing trend over time.[13] The size of public administration has become very comparable across countries in the last period.

Tables 1a and 1b finally report mean weekly earnings of Indian and Chinese wage earners at each period. Note that (weekly) earnings and (weekly) wages are used interchangeably throughout the paper. It is easily verified that the compounded annual growth rate of average earnings between periods 1 (1987–88) and 3 (2002–04) was around 3 percent in India and 7 percent in China. At the same time, the GDP per capita for India (China) was 1,569 (1,528) in period 1 and 2,553 (4,568) in period 3, measured in 2000 PPP USD, which gives a compounded growth rate of around 3.5 percent (8 percent) on average per year. Thus the difference in wage progression between the two countries reflects to some extent differences in overall economic performance; this should appear in some of our results below.[14]

To go beyond average figures, we compute log earnings (in 2000 PPP USD) at different quantiles for each country, as depicted in the two left hand side quadrants of Figure 1. The graphs reflect the fast earnings growth in China and the very modest changes in India previously encountered. Notice that the wage progression in India benefits mostly to the second half of the distribution. In China, wage growth is larger for higher quantiles between periods 1 (1987–88) and 2 (1993–95) but is more equally shared between periods 2 and 3 (2002–04). The right hand side quadrant is simply the difference of the two latter curves, i.e. the Indo-Chinese difference in earnings. It is positive for nearly all deciles of the earnings distribution in periods 1 and 2; however, by period 3, the earnings gap had turned in favor of China for the lower half of the distribution, and was significantly reduced for the upper deciles.

[12]In the recent period, it is a manifestation of a bank-financed investment of RMB 200 billion (about USD 25 billion) in universities since 1998, which supplemented the government's budgetary support of about RMB 150 billion (USD 20 billion) for secondary and higher education (2000 figures).

[13]For the whole selected sample of men and women, the service sector represents 23 percent of the labor force in India and 17 percent for China in the mid-1990s, which can be compared to the figures provided by the KILM database of the ILO (20 and 15 percent, respectively).

[14]The exercise suggested in this paper simply attempts to quantify how much of the cross-country wage differential can be explained by human capital factors as traditionally available in micro data (e.g. education, experience, etc) and returns to these characteristics; yet, workers' skills are only part of the economic factors explaining the productivity of labor. Fully explaining differences in productivity between countries is beyond the scope of this paper and a broader picture would attempt to reconcile micro and macro aspects. We simply refer here to Bosworth and Collins (2008) for a recent study using growth accounting to compare India and China.

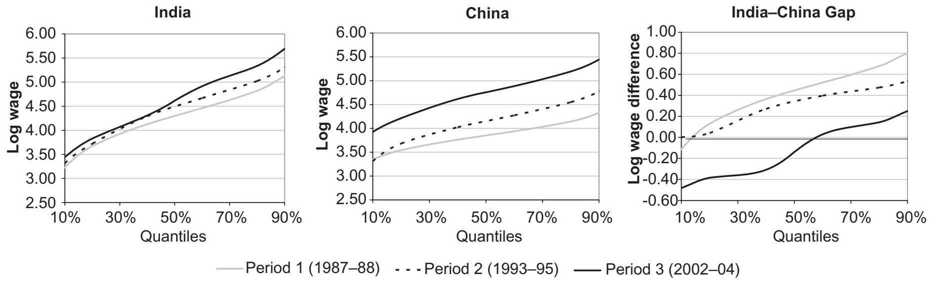

Figure 1. Log-wage Distributions

3. Earnings Equations

We then proceed with the estimation of standard Mincer equations using comparable data and specifications. Following the bulk of the literature, we estimate, for each country and for men and women separately, equations of the form:

$$\ln Y = \alpha_0 + \alpha_1 EXP + \alpha_2 EXP^2 + \sum_i \gamma_i EDUC_i + \sum_j \delta_j CONTROLS_j + \varepsilon \tag{1}$$

where Y is (weekly) earnings, EXP is potential experience, and $EDUC$ is a vector of dummies capturing three different education levels, "no or primary education" being the omitted category (explanations on the construction of EXP and EDUC can be found in Appendix II). Control variables include industry types as previously described ("public administration" is the omitted category). Country-specific controls are also added at this stage, including regional dummies, Han ethnicity and membership of the communist party (for China); and religion dummies and caste-specific public sector jobs (for India).

The Mincer equation (1) is estimated using ordinary least squares (OLS). In addition, we estimate the effects of covariates on earnings at different points of the conditional distribution using quantile regression (QR) (Koenker and Bassett, 1978). Results are typically reported for three points only, namely the 25th centile, the median and the 75th centile. Note that we do not account, in our estimation, 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.[15]

Estimates are reported in Tables A1 to A3 in the Appendix for both countries and for men and women separately. We present only results for the main variable of interests which are common determinants of earnings in both countries, including experience and education (complete results available upon request).

[15]Individual workers in developing countries with surplus labor often do not have the ability to choose between forms of employment; choice of sectors and types of occupation is often accidental and driven by patterns of labor demand (Fields, 2005). Note also that introducing selection in QR decomposition is as yet not common practice (among a few exceptions; see Albrecht *et al.* (2006), who account for female participation decisions).

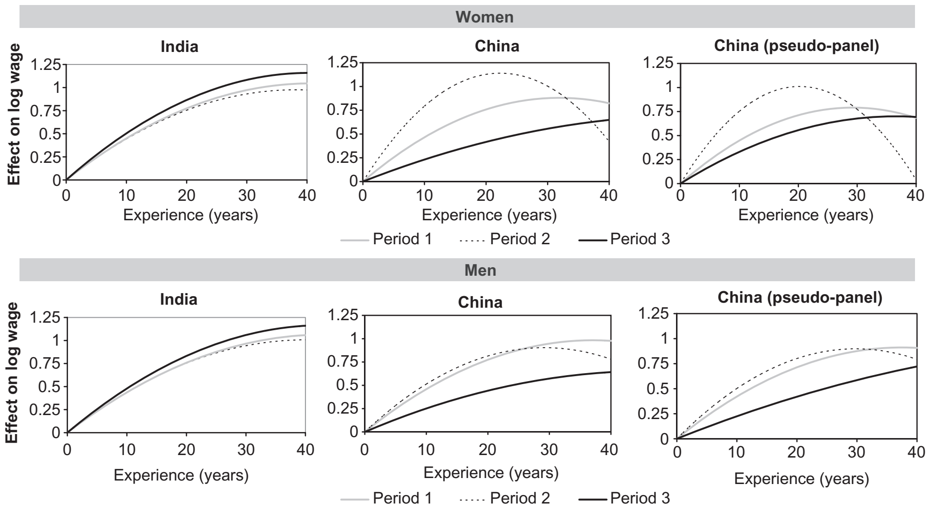

Figure 2. Wage Progression

Corresponding coefficients are mostly significant and R-square values indicate a reasonable degree of fit, of a comparable order to findings by Appleton *et al.* (2005) and Zhang *et al.* (2005) in the case of China, and Duraisamy (2002) and Kijima (2006) for India. These studies provide rich discussions about wage determinants and links to policy and historical developments in the 1980s and 1990s in both countries. Then, to avoid redundant analysis, we simply focus hereafter on returns to experience and education for the sake of the cross-country comparison over time.

Firstly, we use OLS estimates to compute the experience-earnings profile, as plotted in Figure 2. As observed in most countries, this relation has an inverted-U shape. Figure 2 indicates that return to experience was higher, on average, in India than in China, except in period 2 for women with less than 30 years of experience. Returns seem fairly constant in India over time and the cross-country difference in returns between the two countries is, as a result, essentially driven by the trend in Chinese returns. The strong adjustment occurring in China between periods 2 and 3 is expected to appear in our decomposition results and to play in favor of Indian wages.

A specific problem with separate OLS estimations on cross-sectional data is that the age/experience coefficients may capture simultaneously cohort effects and pure experience effects. Considering the important shifts over time in China, it can be suspected that such a problem occurs. To account for this issue, we construct a pseudo-panel by grouping Chinese observations by province, education level and age groups (21–27, 28–34, 35–41, 42–48, 49–54, 55–60), assuming that migration between provinces is small enough not to create significant bias.[16] Results using

[16]For each pseudo-panel observation, we use the average wage as explained variable and include the interaction of time dummies and characteristics (experience and education) as covariates, as well as independent dummies for periods 2 and 3 (i.e. cohort effects are estimated relative to cohort 1). Regressions on these pooled data thus allow separating the experience effect from cohort effects. We thank a referee for suggesting this procedure.

these grouped data for China are depicted in the right-hand side graph of Figure 2; they turn out not to be very different from repeated OLS estimations. That is, a substantial increase in slope and curvature of the profile is observed between the late 1980s and the mid-1990s in China, followed by a sharp decline until 2002. Very similar profiles are actually depicted in Appleton *et al.* (2005).

Then, these important changes must correspond to structural changes in pay policies over time. Knight and Song (2003) argue that the rapid increase between 1988 and 1995 may have been on account of the more experienced workers appropriating a greater than proportionate share of the (ostensibly performance-based) bonuses that were legitimized in the 1980s. Over-rewarding seniority seems to be a central feature of the pre-reform wage structure, resulting in higher returns to experience than in several industrialized countries like the U.K., the U.S. or Australia in the 1980s and 1990s (Meng and Kidd, 1997). Appleton *et al.* (2005) argue that the strong correction that occurred after 1995 was due to the fact that senior workers were the most at risk from retrenchment by enterprises attempting to increase profitability and by the government's initiative to reform and restructure state-owned enterprises (SOE).[17]

Next, we focus on returns to education obtained using both OLS and QR estimations.[18] Results are qualitatively consistent with earlier estimates for both countries (see footnote 2).[19] In Tables A1 to A3 in the Appendix, QR estimates indicate that returns increase consistently with the education level, for both countries, for all time periods, and for all earnings quantiles.

Significant differences between China and India appear in the levels of returns to education and their evolution over time. To make it clear, we plot in Figure 3 the cross-country net difference in returns at each period, for the mean, 25th centile, median and 75th centile. Returns to education are higher in India at all periods and for both men and women, particularly for higher secondary and

[17]As explained by Knight and Song (2003), the fact that the profile peaked earlier in 1995 and fell dramatically for older workers is consistent with a move to a more productivity-based and a less bureaucratically-based earnings structure. The authors also extensively discuss changes in labor market policy and economic structure in China during the 1980s and 1990s and their impact on wage settlements.

[18]We should admit that the coefficient on education obtained from Mincer equations is not an accurate measure of the true rate of return to education. As clarified by Heckman *et al.* (2006), the coefficient only reflects average growth rate of earning with schooling, not the internal rate of return as introduced in the human capital theory. The Mincer coefficient can be regarded as the true return on education only under certain stringent conditions (log earnings function linear in schooling; log-earning-experience profile separable from schooling; no tuition or psychic cost of education; a U-shaped pattern of the variance of earnings over the life cycle). Even when these assumptions are satisfied, bias from omitted variables (ability) in the earnings equation is still an issue (cf. Card, 2001). A strand of literature has been exploring natural experiments, such as birth date (e.g. Angrist and Krueger, 1991), data on twins (e.g. Ashenfelter and Rouse, 1998) or compulsory schooling law (e.g. Oreopoulos, 2006) to identify causality between schooling and earnings and overcome the ability-bias. Nonetheless, given the heterogeneity of the population, as creative as these approaches may be, they can only identify local average treatment effect instead of overall causal relationship for the whole population.

[19]Estimates reported in Tables A1 to A3 are not directly comparable to those of studies using years of schooling as opposed to discrete educational categories (for instance, Zhang *et al.*, 2005, for China). However, results are broadly reconciled if we use an alternative specification using schooling years.

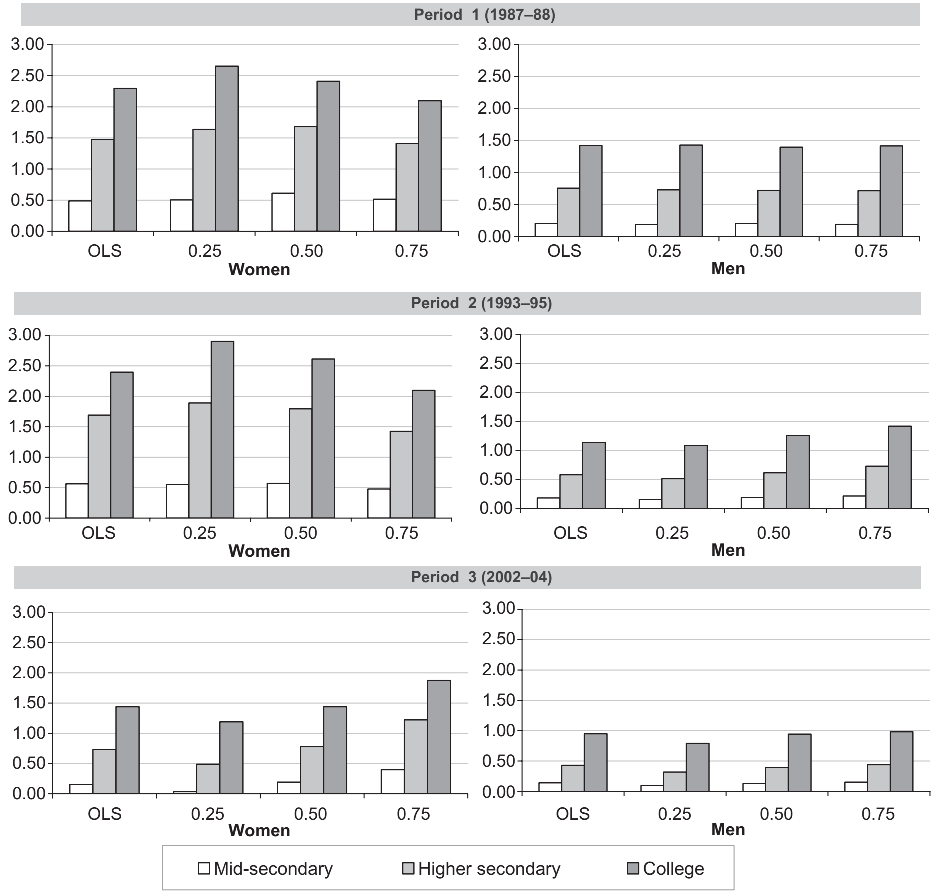

Figure 3. Indo-Chinese Difference in Returns to Education

Note: Ref: no or primary education.

college education.[20] Estimates of Tables A1 to A3 show that returns seem to rise very slowly in India between periods 1 and 2 and even decrease slightly for secondary education between periods 2 and 3. At the same time, returns in China rose by and large, especially for college education and, to a lesser extent, higher secondary education.[21] Men's returns increased gradually over the whole period

[20]These very high returns are partly on account of the rent people with higher education can charge and partly on account of the pattern of industrialization specific to India, that is, service sector and skill intensive sector driven, as opposed to mass manufacturing driven.

[21]These results are consistent with increased demand for skilled labor (in particular due to skill-biased technological change) and with the hypothesis of an increasingly competitive labor market, in connection to the stated policy of the Chinese government to closely link productivity and earnings of wage earners since the 1980s (see Liu, 1998; Maurer-Fazio, 1999; Knight and Song, 2003); other aspects may have come into play, including the liberalization of controls on migration that increased the supply of low-skill labor in urban areas (see Appleton *et al.*, 2005, for a discussion). See Zhang *et al.* (2005) for a complete analysis of the evolution of returns to education over time in China.

under study while women's returns rose especially between periods 2 and 3. These trends result in the differences highlighted in Figure 3, showing that returns to education in China partly catch up over the whole period for men; in the case of women, however, the Indian advantage stagnates (at the top) or even increases (at the bottom) between periods 1 and 2 while it decreases very significantly between the mid-1990 and the early 2000s. For men and women alike, the catching up in Chinese returns to education is especially fast for lower quantiles, which, according to estimates of Tables A1 and A3, is due to increase in Chinese returns but also to decrease in Indian returns at the 25th centile. We can anticipate that in the QR decomposition exercise (cf. Section 5), this trend shall contribute to improve the relative situation of Chinese wage earners, especially in the lower part of the distribution.

4. Decomposing the Mean Wage Differential Between India and China

First, we follow the standard approach of Oaxaca (1973) and Blinder (1973) to decompose the average difference in log earnings between India (I) and China (C) as:

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

where Y denotes weekly earnings, X is a vector of individual characteristics affecting earnings (experience, education, etc), β is a vector of returns to these characteristics. As indicated in equation (2), the decomposition makes use of the sample mean values of all characteristics and of the OLS estimates for the returns to these characteristics. The first term on the right hand side of this equation is typically interpreted as the part of the wage difference in means that is associated with differences in returns to individual characteristics across the two distributions (the coefficient or price effect). The second term is the impact of differences in mean characteristics of the two samples for identical returns (the endowment effect).[22]

Note that estimates used for this purpose are drawn from a slightly different estimation as the one previously discussed. In effect, the decomposition of inter-country differences in (log) earnings requires using a common specification for both countries and necessarily excludes the country-specific factors previously included in the list of controls. The fit of the regression used for the decomposition is consequently smaller than what is reported in Tables A1 to A3 in the Appendix. For instance, OLS estimates for the first period give an R-square of 0.46 with specific controls and 0.45 without, in the case of India, and respectively

[22]The decomposition relies critically on the counterfactual mean $\bar{X}_I'\hat{\beta}_C$, which represents a statistical estimate of the mean wage that people with the characteristics observed in the Indian distribution would have if remunerated according to the returns prevailing in China. It is clear, therefore, that this decomposition is a purely statistical exercise, since the counterfactual component does not account for economic response—in either partial or general equilibrium—to the "change" in returns. This is nonetheless a useful tool to quantify the respective roles of price versus composition effects as well as the specific role of key variables like experience or education.

0.30 and 0.17 for China. The loss in goodness-of-fit is more important in China since regional dummies and communist party membership have significant impact on earnings (cf. Appleton *et al.*, 2005; Zhang *et al.*, 2005). Importantly, we check that coefficients on age and education do not differ significantly when country-specific variables are taken out. We verify this point for all regressions and report two examples in Table A4 in the Appendix. Differences turn out to be insignificant in all cases except one (return to college for Indian male workers at period 3); even in that case, the difference remains small enough not to affect our results.

Decomposition results are reported in Table 2. Using dummy variables for education and industry means that the results should be interpreted relatively to the constant, which incorporates the average effect for the omitted group (primary education, public administration). When pooling the corresponding coefficients into a total education effect and a total industry effect, we nonetheless check that results are not exceedingly sensitive to the choice of the omitted group. Some robustness check is conducted by using schooling years instead of education categories.

The difference in mean (log) wages across countries and its evolution over time reflect the early statistical results of Section 2: the wage differential initially in favor of India has decreased over time and changed sign in the last period. For the *first* period (late 1980s), Table 2 shows that most of the difference seems to be

TABLE 2
Decomposition of the Mean Indo-Chinese Wage Differential

	Women			Men		
	Period 1	Period 2	Period 3	Period 1	Period 2	Period 3
Mean log wage difference	0.13	0.10	–0.35	0.36	0.22	–0.14
	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)
Contribution of coefficients						
Total	0.15	0.11	–0.26	0.40	0.26	–0.01
	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)
Experience	0.04	–0.07	0.38	–0.01	0.02	0.36
	(0.11)	(0.15)	(0.16)	(0.06)	(0.09)	(0.10)
Education	0.68	0.79	0.52	0.40	0.31	0.28
	(0.02)	(0.03)	(0.05)	(0.01)	(0.02)	(0.03)
Industry	–0.27	–0.30	–0.45	–0.10	–0.11	–0.18
	(0.04)	(0.05)	(0.07)	(0.02)	(0.03)	(0.03)
Constant	–0.29	–0.32	–0.71	0.10	0.04	–0.48
	(0.07)	(0.10)	(0.13)	(0.03)	(0.06)	(0.08)
Contribution of characteristics						
Total	–0.03	0.00	–0.09	–0.04	–0.04	–0.13
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Experience	–0.06	–0.13	–0.03	–0.04	–0.02	–0.05
	(0.02)	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)
Education	0.03	0.06	–0.10	0.00	–0.04	–0.08
	(0.01)	(0.02)	(0.03)	(0.00)	(0.01)	(0.01)
Industry	0.01	0.07	0.04	0.00	0.02	0.00
	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)

Notes: Standard errors are in brackets. "Experience" is the combined effect of EXP and EXP^2; "education" is the combined effect of the categorical variables (omitted group: primary education); "industry" is the combined effect of 7 industry dummies (omitted group: public administration).

explained by a price effect in favor of India, mostly driven by much higher returns to education in this country. In the *second* period (mid-1990s), very little change seems to occur for the mean wage difference in the case of women; when using schooling years instead of education categories, however, we find that returns significantly increase in favor of India. For men, the aforementioned increase in Chinese returns to education is responsible for a significant change in the coefficient effect and, as a result, a decrease in the average Indo-Chinese wage difference. The difference in characteristics between Indian and Chinese workers plays no role for women and gives only a very small (but significant) advantage to Chinese wage earners in the case of men. In the *third* period, the reversal of the wage gap in favor of China is mostly on account of the coefficient effect, reinforced nonetheless by a significant change in endowments mainly due to the rapid increase in education levels in China in the late 1990s/early 2000s. The coefficient effect includes a strong decrease in returns to experience in China for both men and women, that is more than compensated by the other coefficients. For women, these "other" effects correspond to an increase in returns to education of Chinese female workers (as documented in the previous section). In Table 2, this is captured both in the education effect and in the constant term (returns for the omitted group, i.e. primary education). Indeed, when using schooling years rather than education categories, we find an even larger drop in the coefficient effect between periods 2 and 3 while the change in the constant is much smaller. For men, unfortunately, most of the reversal in the coefficient effect is due to the unexplained part of the constant term; this result is true whether we use schooling years or educational categories. This point is discussed further in the concluding section. Note that the increase in the constant term, especially strong between 1995 and 2002, also comes up in the estimations of Appleton *et al.* (2005, table 2) using slightly different specification.

Finally, we have repeated the decomposition when excluding SOEs (results available upon request). Results are qualitatively identical in this case, with very small differences in the magnitude of the effects. In particular between periods 2 and 3, changes in the endowment effect in favor of China are slightly larger; also, the effect from lower returns to experience in China over this period is less marked, which may indicate that the post-1995 downward correction on payments for seniority was stronger in SOEs. Nonetheless, it seems difficult to capture in these results the specific effects of SOE reforms.

5. Quantile Regression Decomposition

Since mean characteristics and returns to these characteristics can vary significantly across quantiles for a heterogeneous sample of individuals, it has become stylized in the literature to complete the previous exercise by a decomposition of differences in the entire distribution of wages. Precisely, we suggest hereafter to decompose the differential wage distribution illustrated in Figure 1 into endowment and coefficient effects, in a similar way as was done for the mean difference in equation (2).

A number of decomposition procedures have been suggested to untangle the sources of differences in wage distributions. Popular methods used in the wage inequality literature include the "plug-in" procedure of Juhn *et al.* (1993) based on parametric regressions, and the semi-parametric procedure of DiNardo *et al.* (1996) based on sample reweighting. More recently, quantile-based decomposition methods have been suggested by Machado and Mata (2005) and Gosling *et al.* (2000). As demonstrated by Autor *et al.* (2005), the Machado–Mata approach nests most of the usual approaches and has been increasingly used in recent empirical applications.[23] The general idea is to estimate the whole conditional distribution by quantile regression and then to integrate this conditional distribution over the range of covariates in order to obtain an estimate of the unconditional distribution. It is then possible to estimate counterfactual unconditional distributions to perform usual decompositions, and in particular the two following counterfactuals: (i) the Chinese (log) earnings density function that would arise if Chinese wage earners had the same characteristics as their Indian counterparts (used to compute coefficient effects); and (ii) the density function that would arise if the Indian wage earners had the same returns to characteristics as the Chinese workers (used to compute endowment effects).

However, the Machado–Mata estimator is simulation-based, i.e. it combines quantile regression and bootstrapping to generate the two counterfactual density functions, so that estimations are quite slow. Also, ways to estimate the variance consistently have not been suggested. Recently, Melly (2006) has proposed to use moment conditions in order to derive an analytical estimator for the parameters of interest.[24] This estimator is faster to compute and can be used, in turn, to bootstrap results to provide standard errors. We opt for this approach in this paper.

Unfortunately, none of the above methods can be used to divide up the composition effect into the contribution of each single covariate, as can be done for the mean decomposition using the conventional Oaxaca–Blinder method (cf. Table 2). Machado and Mata (2005) suggest using an unconditional reweighting procedure to compute the contribution of covariate X to the composition effect. Unfortunately, as recently stated by Firpo *et al.* (2007), doing so also changes the distribution of other covariates that are correlated with X. Consequently, in what follows, we simply provide the decomposition of the total endowment and price effects without looking at the specific role of each covariate.

Figures 4a and 4b report the results of the decomposition for all three periods, obtained using the estimator of Melly (2006). Complete decomposition results for the median and the 25th and 75th deciles are reported in Table A5 in the Appendix together with bootstrapped standard errors.

Figures 4a and 4b firstly recall the overall trend encountered in Figure 1: a positive premium for Indian workers is observed in the first period, higher for men than women, and declines over time so that in the last period, Indian wage earners are better off than their Chinese counterpart only at the top of the distribution. The graphs also confirm results from the Oaxaca–Blinder decomposition: the

[23]A detailed description of the estimator and an example of application is provided by Albrecht *et al.* (2003). Its asymptotic properties are studied in Albrecht *et al.* (2006) and Melly (2006).

[24]Results are numerically identical to those obtained with the Machado–Mata estimator if the number of simulations used in the latter procedure goes to infinity.

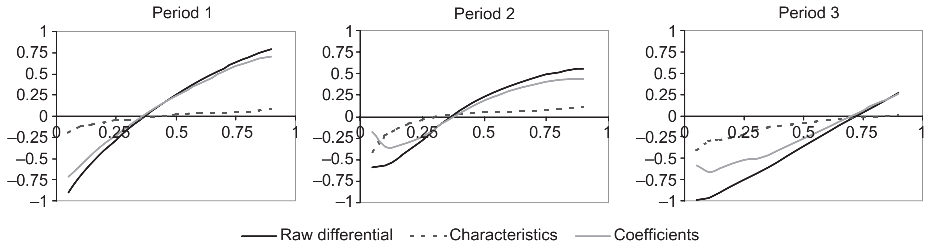

Figure 4a. QR Decomposition (women)

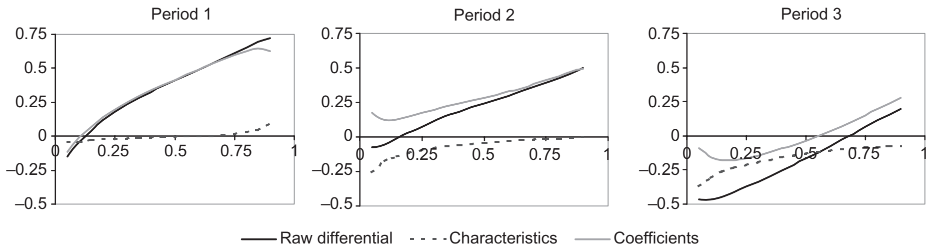

Figure 4b. QR Decomposition (men)

positive wage gap in favor of India is mostly the result of the coefficient effect in the two first periods; there is no significant endowment effect except at the bottom of the distribution. There is little change between periods 1 and 2; we observe only a small narrowing of the cross-country wage gap, especially for top earners—which may be due to increased returns to seniority in China at this period, as previously explained—and stronger for men.

Things change in the third period with a strong decrease in the Indo-Chinese wage gap and a reversal in favor of China for the first three-quarters of the distribution. This shift is due to a combination of price and endowment effects, but the picture is naturally more complex than for the previous mean wage decomposition. Returns to characteristics now play in favor of China for the first half (two-thirds) of the male (female) distribution. This is partly explained by the rapid increase in Chinese returns to education, especially in lower quantiles (see Figure 3); yet, as previously documented, returns are still higher in India in the last period, which conveys that other factors must have come into play to explain the reversal.[25] The endowment effect is particularly strong for men and is unambiguously due to relatively higher education levels in China, especially in the lower part of the distribution. Table A5 in the Appendix confirms that this effect is significantly different from zero up to, at least, the 75th centile. This exercise illustrates the usefulness of the quantile decomposition

[25]As in the OLS decomposition, these unexplained factors must be captured in the intercepts.

approach, which can provide us with a more completed picture than the OLS decomposition. This may also suggest different types of implications regarding the types of policy that could boost earning capacities at different points of the distribution. Results points toward a shortage in educational endowment in India (relatively to China) at the bottom, while relative returns to characteristics decrease over time at the top, which may suggest that the relative quality of education in China has increased.

Arguably, our estimates render only the average effect over all economic sectors while compositions of characteristics and returns to these characteristics may vary from one sector to another. One possibility would be to interact the industry dummies with characteristics like experience and education. We choose instead to replicate the exercise on particular sectors in order to make the cross-country comparison more homogenous while keeping enough heterogeneity in workers' attributes. To balance things, we focus in turn on two sectors that are prominent in one or the other country, but nonetheless large enough to pursue the analysis on large samples. With these constraints in mind, it is fairly natural to focus on the manufacturing sector (in which China is known to have a comparative advantage) and on the service sector (which is more prominent in India).[26] These two sectors are large in both economies—in 2004, the GDP share of the manufacturing (resp. service) sector was 39 percent (resp. 33 percent) in China and 16 percent (resp. 50 percent) in India—and each of them is sufficiently heterogeneous with respect to educational attributes or experience of the laborers.

Results of the decomposition are reported in Figures 5a and 5b for men only (results for women are available upon request). They are qualitatively the same as for the whole urban economy. While endowment effects are virtually the same as before, there are only small differences in levels of the coefficient effects, and consequently of the overall wage gap; this certainly reflects different average productivity levels between countries. We take this result as an interesting robustness check of our more general findings.

6. Concluding Remarks

Despite the near simultaneous rise of China and India as major economic powers, there are few comparative studies of the two countries in terms of wage progression. In this paper, we undertake a comprehensive analysis of the Indo-Chinese wage differential in the urban sector between the late 1980s and the early 2000s. We attempt to describe how earnings distributions compare between countries at three points in time and to which extent "classical" factors (education, experience) explain these differences.

[26]According to Bosworth and Collins (2008), the post-1993 acceleration in growth in China was concentrated mostly in industry, which contributed nearly 60 percent of China's aggregate productivity growth. In contrast, 45 percent of the growth in India in the second sub-period came in services.

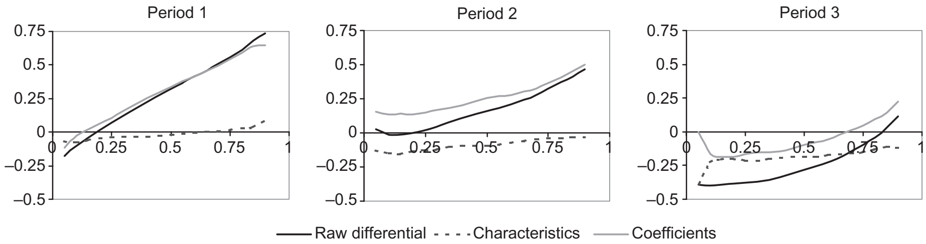

Figure 5a. Decomposition (manufacturing, men)

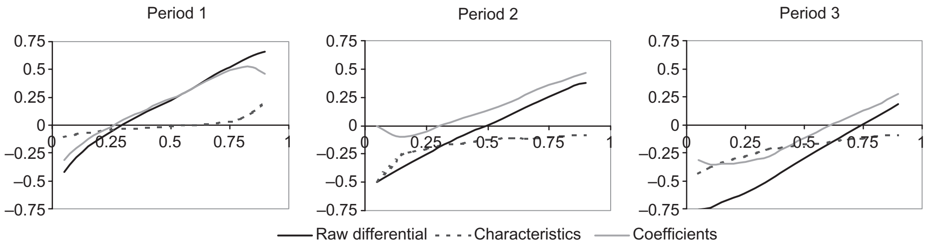

Figure 5b. Decomposition (services, men)

The bulk of the evolution in the Indo-Chinese wage differential seems to be driven by the profound changes that have occurred in China over the past 25 years. Results can be summarized as follows. While Indian wages were higher in the late 1980s, faster productivity growth in China translates into faster wage progression such that, by the early 2000s, the wage gap is reversed in favor of this country at all levels except top earners. Estimate-based decompositions of the wage difference show that in the late 1980s and first half of the 1990s, there is no systematic difference in composition between Indian and Chinese wage earners, and the wage gap is mainly explained by a price effect driven by much higher returns to education in India. Over this period, however, returns to characteristics start to change in favor of China in the upper earnings quantiles. In the late 1990s/early 2000s, the reversal of the wage gap is partly explained by a coefficient effect, and in particular rapidly rising returns to education among Chinese female workers. Interestingly, this reversal is accentuated by an increase in educational endowments in China, mostly in the first half of the earnings distribution. This shows that to some extent, voluntary policy impulse by the Chinese government has had an important effect, especially in improving the earnings capacity of the lower wage workers.

A puzzling aspect is the role of the intercept in the price effects highlighted in our decomposition. Especially between periods 2 and 3, intercepts have increased in both countries, but much faster in China. Even if these terms are arbitrarily defined (in reference to the omitted categories) and difficult to interpret in absolute terms, the cross-country differences may be seen as reflecting unexplained productivity differences and in particular the faster growth in labor

Figure 6. Other Indo-Chinese Comparisons of Wages and Labor Productivity
Source: KILM dataset from the International Labor Organization.

productivity in China. Additional variables that could explain some of this "average" effect may not be easily introduced in this type of regression.[27] This is in particular the case of institutional changes during the 1990s reform in China; better "average" performances in China are also attributed to higher capital intensity in the production processes and the more rapid total factor productivity (TFP) growth since the mid-1990s.[28] This could be seen as a limit to the exercise suggested in this paper. We believe, however, that the vocation of Mincer equation is maybe more to isolate the role of classical human capital variables (and their relative role in explaining wage differential across countries) than to explain labor productivity comprehensively. Nonetheless, and despite these difficulties, further research should attempt to better link micro and macro explanations to labor productivity. In Figure 6, we simply illustrate this point by plotting manufacturing wage indices and the GDP/capita for both countries over time. These alternative measures clearly show that the cross-country productivity gap has reversed in favor of China in the late 1980s, quickly followed by a reversal of the wage gap, and that these gaps have increased since then.

[27]As argued in the text, one of the difficulties is the necessity to use a common set of covariates in Oaxaca–Blinder decompositions, which prevents use of important country-specific variables and necessarily reduces the fit of the Mincer model at use.

[28]According to Bosworth and Collins (2008), slower TFP growth in India (compared to China and compared to the previous period) is due in part to rigid labor laws, which prevent the most efficient use of workers, and to a lack of modern infrastructure. Note also that our results in the last section, and in particular similar results in industry and service, convey that the rising tide lifts all boats in China. Even in the service sector, China seems to be more productive in the recent period (cf. also Bosworth and Collins, 2008), which drives the pattern in the Indo-Chinese differential of Figure 5b.

Appendix I: Empirical Results

TABLE A1
Estimates of Mincer Equation (Period 1: 1987–88)

	Women				Men			
Coeff.	OLS	25%	50%	75%	OLS	25%	50%	75%
India								
Experience	0.05***	0.07***	0.04***	0.04***	0.05***	0.06***	0.05***	0.04***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience sq./100	–0.07***	–0.09***	–0.05***	–0.04***	–0.06***	–0.07***	–0.05***	–0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Mid-secondary	0.64***	0.66***	0.74***	0.63***	0.24***	0.25***	0.24***	0.23***
	(0.06)	(0.10)	(0.06)	(0.07)	(0.01)	(0.02)	(0.01)	(0.01)
Higher secondary	1.24***	1.40***	1.29***	1.09***	0.64***	0.66***	0.62***	0.61***
	(0.04)	(0.06)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
College	1.74***	1.94***	1.71***	1.54***	1.11***	1.12***	1.09***	1.11***
	(0.04)	(0.07)	(0.04)	(0.05)	(0.01)	(0.02)	(0.01)	(0.01)
Constant	2.59***	1.94***	2.68***	3.22***	3.19***	2.88***	3.26***	3.54***
	(0.07)	(0.11)	(0.07)	(0.08)	(0.03)	(0.03)	(0.03)	(0.03)
Pseudo-R^2	0.46	0.31	0.31	0.26	0.39	0.24	0.26	0.27
China								
Experience	0.05***	0.06***	0.05***	0.04***	0.05***	0.05***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience sq./100	–0.08***	–0.09***	–0.08***	–0.05***	–0.07***	–0.07***	–0.05***	–0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mid-secondary	0.15***	0.16***	0.13***	0.12***	0.03**	0.06***	0.04***	0.04**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Higher secondary	0.26***	0.27***	0.23***	0.19***	0.09***	0.11***	0.10***	0.09***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
College	0.42***	0.42***	0.37***	0.34***	0.24***	0.24***	0.21***	0.21***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	2.76***	2.54***	2.88***	3.20***	3.05***	2.84***	3.12***	3.33***
	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
Pseudo-R^2	0.37	0.20	0.19	0.18	0.36	0.26	0.22	0.19

Notes: Asterisks report the level of significance (***: 1%, **: 5%, *: 10%) and standard errors are in brackets. Omitted category for education is "no or primary education." Common control is industry type (the omitted group is "Public administration"). Specific controls are: regions, Han ethnicity, member of communist party (for China); religion dummies and caste-specific public sector jobs (for India).

TABLE A2

Estimates of Mincer Equation (Period 2: 1993–95)

Coeff.	Women OLS	Women 25%	Women 50%	Women 75%	Men OLS	Men 25%	Men 50%	Men 75%
India								
Experience	0.05***	0.07***	0.05***	0.03***	0.05***	0.06***	0.05***	0.04***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience sq./100	–0.06***	–0.10***	–0.06***	–0.03***	–0.06***	–0.08***	–0.05***	–0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Mid-secondary	0.64***	0.72***	0.73***	0.64***	0.28***	0.27***	0.28***	0.27***
	(0.08)	(0.10)	(0.07)	(0.06)	(0.02)	(0.02)	(0.01)	(0.01)
Higher secondary	1.36***	1.69***	1.54***	1.26***	0.60***	0.61***	0.62***	0.62***
	(0.05)	(0.07)	(0.04)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
College	1.75***	2.15***	1.91***	1.63***	1.08***	1.14***	1.15***	1.13***
	(0.05)	(0.07)	(0.05)	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Constant	2.46***	1.68***	2.45***	3.17***	3.18***	2.92***	3.29***	3.64***
	(0.09)	(0.13)	(0.08)	(0.07)	(0.04)	(0.04)	(0.03)	(0.03)
Pseudo-R^2	0.36	0.29	0.32	0.27	0.26	0.22	0.26	0.28
China								
Experience	0.10***	0.11***	0.07***	0.05***	0.06***	0.06***	0.04***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience sq./100	–0.22***	–0.25***	–0.16***	–0.10***	–0.11***	–0.10***	–0.06***	–0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Mid-secondary	0.08*	0.16***	0.16***	0.16***	0.10**	0.12***	0.10***	0.06
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
Higher secondary	0.23***	0.35***	0.32***	0.31***	0.20***	0.25***	0.19***	0.10***
	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
College	0.48***	0.59***	0.52***	0.48***	0.35***	0.41***	0.32***	0.23***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
Constant	2.66***	2.14***	2.87***	3.38***	3.04***	2.81***	3.29***	3.71***
	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)	(0.06)
Pseudo-R^2	0.68	0.19	0.18	0.18	0.57	0.16	0.17	0.17

Notes: Asterisks report the level of significance (***: 1%, **: 5%, *: 10%) and standard errors are in brackets. Omitted category for education is "no or primary education." Common control is industry type (the omitted group is "Public administration"). Specific controls are: regions, Han ethnicity, member of communist party (for China); religion dummies and caste-specific public sector jobs (for India).

TABLE A3

Estimates of Mincer Equation (Period 3: 2002–04)

	Women				Men			
Coeff.	OLS	25%	50%	75%	OLS	25%	50%	75%
India								
Experience	0.05***	0.07***	0.04***	0.04***	0.05***	0.06***	0.05***	0.05***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Experience sq./100	–0.07***	–0.10***	–0.04***	–0.04***	–0.06***	–0.08***	–0.05***	–0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Mid-secondary	0.41***	0.36***	0.46***	0.55***	0.25***	0.22***	0.30***	0.29***
	(0.08)	(0.11)	(0.08)	(0.10)	(0.02)	(0.03)	(0.02)	(0.03)
Higher secondary	1.09***	1.04***	1.14***	1.24***	0.55***	0.51***	0.58***	0.58***
	(0.06)	(0.08)	(0.07)	(0.08)	(0.02)	(0.03)	(0.02)	(0.03)
College	1.70***	1.69***	1.71***	1.75***	1.21***	1.11***	1.23***	1.25***
	(0.06)	(0.08)	(0.07)	(0.09)	(0.02)	(0.03)	(0.03)	(0.03)
Constant	3.29***	2.83***	3.50***	3.71***	3.70***	3.46***	3.69***	4.01***
	(0.13)	(0.17)	(0.14)	(0.17)	(0.05)	(0.07)	(0.05)	(0.06)
Pseudo-R^2	0.50	0.32	0.35	0.31	0.48	0.28	0.34	0.33
China								
Experience	0.03***	0.03***	0.02***	0.02***	0.03***	0.04***	0.02***	0.02***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experience sq./100	–0.03***	–0.05***	–0.01	–0.02	–0.04***	–0.05***	–0.03***	–0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mid-secondary	0.25***	0.33***	0.27***	0.15*	0.11**	0.12**	0.17***	0.13**
	(0.07)	(0.09)	(0.07)	(0.08)	(0.05)	(0.06)	(0.05)	(0.07)
Higher secondary	0.51***	0.59***	0.55***	0.42***	0.26***	0.29***	0.32***	0.29***
	(0.07)	(0.09)	(0.07)	(0.08)	(0.05)	(0.06)	(0.05)	(0.07)
College	0.84***	0.96***	0.86***	0.70***	0.54***	0.54***	0.55***	0.56***
	(0.07)	(0.09)	(0.07)	(0.08)	(0.05)	(0.06)	(0.06)	(0.07)
Constant	3.68***	3.31***	3.75***	4.16***	3.92***	3.63***	3.98***	4.30***
	(0.09)	(0.12)	(0.09)	(0.11)	(0.07)	(0.09)	(0.08)	(0.09)
Pseudo-R^2	0.53	0.18	0.20	0.19	0.50	0.18	0.18	0.19

Notes: Asterisks report the level of significance (***: 1%, **: 5%, *: 10%) and standard errors are in brackets. Omitted category for education is "no or primary education." Common control is industry type (the omitted group is "Public administration"). Specific controls are: regions, Han ethnicity, member of communist party (for China); religion dummies and caste-specific public sector jobs (for India).

TABLE A4

Sensitivity to the Use of Country-Specific Controls

Country-specific controls	Period 1, Female Workers						Period 3, Male Workers					
	India			China			India			China		
	No	Yes	Δ	No	Yes	Δ	No	Yes	Δ	No	Yes	Δ
Experience	0.051	0.051	0.000	0.055	0.052	−0.004	0.054	0.053	−0.001	0.028	0.031	0.003
	(0.004)	(0.004)	(0.005)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)
Experience sq./100	−0.067	−0.067	0.000	−0.087	−0.081	0.006	−0.063	−0.062	0.001	−0.030	−0.045	−0.014
	(0.007)	(0.007)	(0.010)	(0.005)	(0.004)	(0.007)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.010)
Mid-secondary	0.626	0.637	0.011	0.126	0.149	0.023	0.276	0.253	−0.023	0.157	0.111	−0.046
	(0.062)	(0.062)	(0.088)	(0.015)	(0.014)	(0.021)	(0.022)	(0.022)	(0.031)	(0.056)	(0.052)	(0.076)
Higher secondary	1.215	1.241	0.026	0.251	0.256	0.005	0.591	0.553	−0.039	0.348	0.265	−0.083
	(0.038)	(0.040)	(0.055)	(0.017)	(0.016)	(0.023)	(0.020)	(0.020)	(0.029)	(0.057)	(0.053)	(0.078)
College	1.698	1.737	0.039	0.437	0.424	−0.013	1.272	1.206	−0.066	0.648	0.543	−0.104
	(0.040)	(0.042)	(0.058)	(0.022)	(0.021)	(0.031)	(0.022)	(0.023)	(0.031)	(0.058)	(0.055)	(0.080)

Notes: Standard errors are reported in brackets.

TABLE A5

QR Decomposition

	Period 1			Period 2			Period 3		
	25%	50%	75%	25%	50%	75%	25%	50%	75%
Women									
Raw differential	−0.28	0.25	0.62	−0.26	0.22	0.48	−0.74	−0.36	0.04
Characteristics	−0.05	0.01	0.04	−0.04	0.04	0.08	−0.22	−0.09	−0.02
	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.06)	(0.02)	(0.01)
Coefficients	−0.23	0.24	0.58	−0.22	0.18	0.40	−0.52	−0.27	0.06
	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.06)	(0.04)	(0.03)
Men									
Raw differential	0.18	0.41	0.61	0.08	0.24	0.39	−0.36	−0.17	0.05
Characteristics	−0.02	0.00	0.02	−0.09	−0.04	−0.02	−0.19	−0.13	−0.09
	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Coefficients	0.20	0.41	0.60	0.17	0.28	0.41	−0.17	−0.03	0.14
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)

Notes: In brackets, we report the standard errors of the coefficient effects, estimated by bootstraping the results 100 times.

Appendix II: Construction of Education Variables

Education Systems in India and China

In India, the education can be divided into five stages: pre-primary education, primary school, middle school, secondary and higher secondary school, and college education. The pre-college education involves general education. Most states follow five years of primary education (four years in Assam, Gujarat, Karnataka, Kerala, Maharashtra and West Bengal), three years of middle school education (four in West Bengal), four years of secondary and higher-secondary levels, and three years of college.

In China, the education can be divided into five stages: pre-primary education, primary school, junior high school, senior high school, and post-high school education (college education). As in India, the pre-college focuses on general education. In China, the primary school lasts six years, junior high school education three years, senior high school another three years, and college four years.

Education Variables

The Indian NSS data only reports categorical variables. On top of this, the number of years of education may not be extremely meaningful when comparing India and China. Mainly for these reasons, our analysis mostly relies on categorical education variables instead of continuous measures of schooling. The use of education categories, while somewhat unusual in the Chinese context, can be found in other studies (e.g. Liu, 1998). Nonetheless, we also make use of education levels in years to construct the proxy measure for experience, *EXP*, computed as age minus schooling minus six (years prior to school enrolment). The exercise that consists of translating education levels into schooling years is complicated by the fact that there is variation across states in India; we have followed the approach of Kijima (2006) to obtain consistent measures.

We now discuss how educational categories have been constructed. Using country-specific categories, as those detailed above, would naturally hinder any form of comparison. For that purpose, we have constructed relatively broad categories, defined as follows. The first one is "no education" or "primary education," which includes people having finished primary school or below. The second category is "middle secondary education," which includes people who finished only up to middle school in India and junior high school in China. The third category is "high secondary education," which includes the Indians who finished secondary and higher secondary education and the Chinese who finished senior high school. The fourth category, denoted "college education," includes all those who had at least some post-secondary education, including engineers and medical students.

This way, we hope to capture broad differences in workers' skills which are somewhat comparable across countries, even if not perfectly identical. If more precise categorical variables—such as those defined at the national level in the above description—were perfectly overlapping across countries, it is likely that differences in quality of schooling would remain an issue so that comparisons would still not be perfect. Further discussions about cross-country comparisons of returns to education can be found in Trostel *et al.* (2002). It is worth noting that quality of education can also be different among regions within a country.[29]

The problem of school quality has received much emphasis in the literature on India (e.g. Drèze and Sen, 2002). The implicit assumption made in our work is that errors within each educational category are similar in successive NSS surveys—so that comparisons of returns to education over time, within each country, are plausible.

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[29]As noticed by a referee, the fraction of Indian schools that have an average pupil/teacher ratio over 50 is 2.2 percent in the state of Kerala and 0.2 percent in Goa, but reaches 58 percent in Uttar Pradesh and 78.8 percent in Bihar (cf. 7th All India School Education Survey, http://www.7thsurvey.ncert.nic.in/).

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