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Changes in Wage Structure in Urban India, 1983–2004: A Quantile Regression Decomposition

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Summary. — This paper utilizes individual level earnings data from urban India to examine the evolution of wages during 1983–2004 across the entire wage distribution. Quantile regression analysis reveals that the effects of many covariates are not constant across distribution. Returns to secondary and tertiary education not only increased in the 1990s but also became more heterogeneous suggesting wage inequality may increase further in near future as more workers get higher education. Moreover, the quantile regression decomposition suggests that the increase in returns has been the driving force behind the increase in wages in both the 1980s and 1990s.
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Key words — earning functions, Asia, India, quantile regression, decomposition, wage inequality

1. INTRODUCTION

In this paper, we examine changes in the wage structure in urban India across the entire wage distribution over the past two decades (1983–2004). We investigate the earnings function at three points in time (1983, 1993, and 2004) using ordinary least squares and quantile regressions to assess whether the entire earnings distribution is affected uniformly by human capital variables, demographic characteristics, and industry affiliations. We also investigate the changes in returns to various characteristics over 1983–93 and 1993–2004. Furthermore, we apply a quantile regression based decomposition method proposed in Machado and Mata (2005) to evaluate the role of changing work force composition (in terms of workers' characteristics) and changing labor market prices in overall changes in the wage distribution over these two time periods. Changes in work force composition can raise or lower overall earnings dispersion by increasing or reducing heterogeneity in observed skills (e.g., education and experience), and wage dispersion may change due to mechanical impact of composition without any underlying changes in market prices. In contrast, without any changes in the composition of work force, earning dispersion may increase or decrease if market prices paid within the same skill group (for example higher educated works) becomes more/less heterogeneous or market price of different skill groups changes.

There has been a growing interest in wage inequality in India as Indian economy has been among the fastest growing economies in the developing world since the 1980s, and India initiated economic liberalization in 1991 that abolished the four decade old import-substitution industrialization strategy, and initiated a drastic liberalization of the external sector and industrial policy. The existing literature, based on data from 1983 to 1999, points out that the economic growth in the past two decades has been associated with rising wage inequality (Dutta, 2005; Kijima, 2006). Dutta (2005) examines trends in wage dispersion during 1983–99 using various indices and a regression-based decomposition, and finds that wage inequality increased during 1983–99. Kijima (2006) examines changes in wage inequality in urban India during 1983–99 using the Juhn, Murphy, and Pierce (1993) method, and finds that wage inequality in urban India started increasing before 1991. He attributes the increase in wage inequality over

1983–99 to an increase in the returns to tertiary education. Chamarbagwala (2006) uses the demand and supply framework of Katz and Murphy (1992) and finds that the skill premium in India increased during 1983–99, and attributes this increase to skill biased technological change.

A shortcoming of the existing literature on wages in India is that it primarily concentrates on averages, neglecting the rest of the distribution.¹ While market-oriented economic reforms initiated in the 1980s and accelerated in the 1990s, are widely believed to lie behind the high growth, there is a considerable concern that the main beneficiaries of recent growth have been those at the higher end of the distribution (Cain, Hasan, Magsombol, & Tandon, 2010). The existing literature because of their concentration on averages could not address the concerns whether it is the higher end of the distribution who is the main beneficiary of recent growth. Furthermore, it is important to go beyond averages to present a complete picture for three reasons. First, recent works in other countries using quantile regression techniques have shown that attributes have different effect on the wages of individuals at the top of the wage distribution compared with individuals at the bottom of the wage distribution.² Second, India is a heterogeneous society in the midst of rapid change. This suggests that effects may be heterogeneous as well. Third, there is growing evidence from other countries (e.g., the US) that suggests that, far from being ubiquitous, the growth in wage inequality is increasingly concentrated in the top end of the wage distribution (Lemieux, 2008).

This paper contributes to the existing literature in the following way. First, we estimate earning functions across the entire wage distribution using quantile regression, and analyze the changes in the contribution of individual covariates over time. Second, we decompose the change in wages in the past two decades into a part that is attributable to a change in prices (the coefficient effect) and a part that is

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attributable to a change in characteristics (the covariate effect) across the entire wage distribution. Third, we extend the existing literature through 2004 by incorporating new data.

The findings of the paper are as follows. First, during 1983–93, there was simultaneous expansion of lower (50–10 wage gap) and upper tail (90–50 wage gap) inequality. However, between 1993 and 2004, the upper tail inequality expanded while lower tail inequality contracted. Second, the wage changes are driven mostly by an increase in prices paid (coefficient effect) across the entire wage distribution in both decades. Also, this coefficient effect is larger at higher quantiles. The change in the composition of the work force (covariate effect) contributed positively between 1983 and 1993; its contribution to the wage growth was negative between 1993 and 2004 – if there had been no changes in prices paid between 1993 and 2004, the changing composition of workforce may have led to decrease in wages. Third, returns of many characteristics are not homogeneous in the 3 years of study. The returns to higher education (secondary and tertiary) not only increased during the 1990s but also became more heterogeneous across quantiles – returns were higher at the higher quantiles.

The findings of the paper suggest that wage inequality in urban India will continue to increase in the near future as educational composition changes over time and more workers obtain higher education especially tertiary education. Since returns to tertiary education not only have increased but also have become more heterogeneous over the last decade, it will add to both within and between group inequality in the near future. However, the increase in skill premium during the 1990s is expected to stimulate further increases in human capital investment (Topel, 1999), and an increase in the number of college graduates may decrease the wage inequality in the long run as South Korea experienced in 1970s and 1980s (Kim & Topel, 1995).

The remainder of the paper is organized as follows. Section 2 deals with the empirical strategy, Section 3 describes the data, Section 4 investigates the results, and Section 5 concludes.

2. EMPIRICAL STRATEGY

(a) Quantile regression

Let $Q_\theta(w|x)$ for $\theta \in (0, 1)$ denote the θ th quantile of the distribution of the log wage given the vector of covariates x . We model the conditional quantile as:

$$Q_\theta(w|x) = x'\beta(\theta) \quad (1)$$

where $\beta(\theta)$ is a vector of quantile regression (QR) coefficients (Koenker & Bassett, 1978).

(b) Decomposition of differences in wage distributions

We would like to perform Oaxaca-Blinder (which decomposes the difference in averages) type decomposition across the entire wage distribution. A number of decomposition procedures have been suggested to untangle the sources of differences between wage distributions. Popular methods used in the wage inequality literature include the “plug-in” procedure of Juhn et al. (1993, JMP hereafter) based on parametric regressions, the reweighting procedure of DiNardo, Fortin, and Lemieux (1996), and more recently a quantile regression based decomposition method of Machado and Mata (2005). The limitation of the JMP (1993) methodology is that it is valid only in the case of homoskedasticity, which is usually rejected for empirical wage distributions. In addition, it is restrictive as it assumes a single linear model to hold for the entire distribu-

tion. The limitation of the DiNardo et al. (1996) technique is that it allows one to investigate the role of changes in endowments only.³ In addition, it relies on OLS regressions to do quantile analysis.

In this paper, we apply the Machado and Mata (2005, MM hereafter) technique. The advantage of the MM technique is that the quantile regressions account for heteroskedasticity, and it partitions the observed difference in wage distributions into “price” and “quantity” components. The MM (2005) decomposition is well suited to depict heterogeneous characteristic and coefficient effects across the entire distribution. As demonstrated by Autor, Katz, and Kearney (2005), the MM approach nests most of the usual approaches.

The idea underlying the MM technique is that the conditional quantiles of w , given by Eqn (1), can be estimated by quantile regression. If Eqn (1) is correctly specified, the conditional quantile process – that is, $Q_\theta(w|x)$ as a function of $\theta \in (0, 1)$ – provides a full characterization of the conditional distribution of wages given x . The estimated conditional quantile function parameters can be used to simulate the conditional distribution of w given x via an application of the probability integral transformation theorem. The algorithm below summarizes the procedure.

1. For each year, $\tau = 1983, 1993, 2004$, we estimated 999 quantile regressions on a fine grid of quantiles, $\theta = [0.001, 0.002, \dots, 0.998, 0.999]$

$$Q_{\theta_i}(w|x; \tau)$$

which yields 999 estimates of the QR coefficients $\hat{\beta}_\tau(\theta_i)$ for each year.⁴

2. Then we draw $m = 1000$ random draws with replacement from the distribution of covariates for each $\hat{\beta}_\tau(\theta_i)$'s and stack $x'_\tau \hat{\beta}_\tau(\theta_i)$ to get the marginal distribution which conforms to our model.⁵

$$w^* = \{x_i^*(\tau)' \hat{\beta}_\tau(\theta_i)\}_{i=1}^{999}$$

3. To construct the counterfactual density, i.e., the density function of wages in year 1, corresponding to the year 0 distribution of the covariates, we take $\hat{\beta}_\tau(\theta_i)$ estimated from the period 1 sample, and instead of drawing from the distribution of covariates from period 1 sample, we draw it from the rows of the period 0, i.e. $x(0)$.

Let $f(w(1))$ denote the estimate of the marginal density of w (log of wages) in year 1 based on observed sample, i.e., the empirical density, and $F^*(w(1))$ denote an estimate of the density of w in year 1 based on the generated sample $w^*(1)$, i.e., the marginal implied by the model. Extending this notation to the counterfactual distributions, we may define $F^*(w(1); x(0))$ as the density that would have prevailed in year 1 if all covariates would have been distributed as in year 0, but the workers were paid as in year 1. We may use the counterfactual distribution, $f^*(w(1); x(0))$, to decompose the changes in wage distributions between any 2 years.⁶ Letting α be a usual summary statistic (for instance, quantile or scale measure), we may decompose differences in α as:

$$\begin{aligned} \alpha\{f(w(1))\} - \alpha\{f(w(0))\} \\ = \alpha\{f^*(w(1))\} - \alpha\{f^*(w(0))\} + \text{residual} \\ = \alpha\{f^*(w(1))\} + \alpha\{f^*(w(1); x(0))\} \\ - \alpha\{f^*(w(1); x(0))\} - \alpha\{f^*(w(0))\} + \text{residual} \\ = \left\{ \frac{\alpha\{f^*(w(1))\} - \alpha\{f^*(w(1); x(0))\}}{\text{covariate effect}} \right\} \\ + \left\{ \frac{\alpha\{f^*(w(1); x(0))\} \alpha\{f^*(w(0))\}}{\text{coefficient effect}} \right\} + \text{residual \quad (2)} \end{aligned}$$

This decomposition will then give us the contribution of the covariates, the coefficients, and an unexplained part (residual). The residual is the difference that is unaccounted by the estimation method (estimated as the difference between the estimates of the total changes provided by using the empirical wage density and by using the estimated marginal densities).⁷

3. DATA

The analysis in this paper draws on individual level data from the Employment and Unemployment Schedule, administered by the National Sample Survey Organization (NSSO), Government of India. We use data from the 38th, 50th, and 61st rounds which were conducted in 1983, 1993–94, and 2004–05, respectively (referred to as 1983, 1993, and 2004 in this paper).⁸ The data constitute a repeated cross section and contain information on household size and composition, social group, religion, monthly consumption, landholdings, demographic variables (age, gender, marital status), educational participation and attainment, along with a detailed employment section on principal and subsidiary activities (industry, occupation, and wages earned). The sample is drawn based on a stratified random sampling procedure and all the analysis is done using survey weights.

In the data, workers are classified as self-employed, regular wage/salaried, and casual labor. Weekly wages earned are reported at current prices only for regular wage/salaried and casual labor.⁹ In rural India, only about 10% of the male workers have regular salaried jobs compared to 48% of male workers in urban India (Table 1), while 30% of rural male workers are casual compared to about 13% in urban areas. Given the very thin nature of regular employment in rural India, we concentrate on urban labor market.¹⁰ As earnings for self-employed are not reported, our sample excludes self-employed workers.¹¹ We also restrict our attention to only male workers in age 21–60.¹² Hence our final sample consists of urban male wage workers (both wage/salaried and casual workers) in age 21–60.

In this paper, we do not address selection into wage labor for three reasons. First, the technique required to correct for selectivity bias in quantile regression models is less well developed.¹³ Second, even if one could adequately address nonrandom sample selection, we are only interested in describing the wage distribution conditional on being in wage employment. Third, since we are comparing the same urban labor market over time, and the share of wage workers in

the relevant population has not changed much during the time period under study, it is unlikely that a standard correction for sample selection would significantly affect our decomposition results.

Reported weekly wages are deflated to 1984–85 prices using the state-specific consumer price index for urban nonmanual employees. The spatial differences in cost of living in each year are adjusted using the ratio of the official state-specific urban poverty line to the all India urban poverty line. The 1983 and 1993 data use National Industrial Classification codes (NIC) – 1970 and 1987, respectively, to report industry of employment at three digits, while 2004 data use NIC-1998 to report industry of employment at five digits. Uniformity is established across the three surveys using a concordance table and 24 broad industries are created.

Our dependent variable is log of real weekly wage, and the covariate matrix x includes age, age squared, dummies for states, education levels, public-sector employment, married, the Scheduled Castes (SCs), the Scheduled Tribes (STs), Muslims, and industries.¹⁴ x matrix also includes an indicator for casual labor and interaction of casual labor with the education dummies.¹⁵ The introduction of casual labor and its interaction term addresses the fact that casual workers may have different returns compared to regular salaried workers. The SCs and the STs are two historically disadvantaged groups, and enjoy the benefit of affirmative action taken by Government of India in the form of reservation in jobs and education. Muslims constitute the largest religious minority group in India.¹⁶ A dummy for public employment is included as the wage settings are different in public sector compared to private sector. While private sector wages are determined by competitive forces, the government sets wages in the public sector through

Table 2. Descriptive statistics of sample

| Variable/year | 1983 | 1993 | 2004 |
|---|--------------------|--------------------|--------------------|
| Weekly wage | 149.30 (152.94) | 213.90 (177.17) | 289.46 (359.40) |
| Log of real weekly wage | 4.76 (0.72) | 5.04 (0.92) | 5.26 (0.89) |
| <i>Percentile differential in log real wage</i> | | | |
| 90–10 | 1.77 | 2.05 | 2.29 |
| 90–50 | 0.77 | 0.95 | 1.33 |
| 75–50 | 0.40 | 0.53 | 0.79 |
| 75–25 | 0.91 | 1.11 | 1.31 |
| 50–25 | 0.51 | 0.58 | 0.52 |
| 50–10 | 1.00 | 1.10 | 0.96 |
| Age | 35.71 (9.96) | 36.72 (9.87) | 36.51 (10.22) |
| Public sector worker | NA | 32.18 | 26.90 |
| Regular salaried | 77.88 | 75.89 | 76.11 |
| Casual labor | 22.12 | 24.11 | 23.89 |
| <i>Education levels (percentage in wage workers)</i> | | | |
| Illiterates | 18.89 | 16.34 | 12.02 |
| Below primary | 11.1 | 10.35 | 7.85 |
| Primary | 15.81 | 12.42 | 12.71 |
| Middle | 17.2 | 16.18 | 18.15 |
| Secondary | 23.11 | 26 | 28.36 |
| Tertiary | 13.89 | 18.7 | 20.9 |
| <i>Demographic variables (percentage in wage workers)</i> | | | |
| Scheduled castes | 13.64 | 14.64 | 17.31 |
| Scheduled tribes | 3.81 | 3.40 | 3.22 |
| Muslims | 11.14 | 10.23 | 11.30 |
| Sample size | 27,021 | 28,129 | 25,618 |

Table 1. Distribution of male workers aged 21–60

| | Regular salaried | Casual | Self-employed | Total workers |
|------|---------------------|-------------------|-------------------|-------------------|
| 1983 | Rural | 9,235 (10.65) | 23,580 (31.01) | 50,453 (58.33) |
| | Urban | 21,430 (48.05) | 5,591 (13.64) | 18,221 (38.31) |
| 1993 | Rural | 9,199 (9.88) | 21,329 (34.79) | 46,624 (55.33) |
| | Urban | 21,901 (45.56) | 6,228 (14.48) | 20,105 (39.97) |
| 2004 | Rural | 13,614 (9.93) | 19,273 (32.98) | 55,900 (57.08) |
| | Urban | 18,751 (42.35) | 6,867 (13.29) | 22,350 (44.36) |
| | | | | 88,787 |
| | | | | 47,968 |

Notes: The sample is restricted to male workers in age group 21–60. Sample size is reported in the first line. Percentages are calculated using survey weights and are shown in parentheses.

Notes: (1) Standard deviation in parentheses.

(2) Real wages in Indian Rupees at 1984–85 prices.

Table 3. *Shares of different industries in wage workers in urban India*

| | 1983 | 1993–94 | 2004–05 | Change in share during 2005 and 1983 |
|--|------|---------|---------|--------------------------------------|
| Agriculture, hunting, forestry, and fishing | 5.5 | 5.6 | 3.2 | -2.3 |
| Mining and quarrying | 2.1 | 2.2 | 1.8 | -0.3 |
| Manufacture of food, beverage, and tobacco products | 3.2 | 2.6 | 2.1 | -1.1 |
| Manufacture of textiles, leather, fur, wearing apparel, and footwear | 10.4 | 7.6 | 8.7 | -1.7 |
| Manufacture of wood and wood products | 1.3 | 1.0 | 3.2 | 2.0 |
| Manufacture of paper, paper products, printing, and publishing | 1.3 | 1.2 | 1.6 | 0.2 |
| Manufacture of chemicals, rubber, plastic, petroleum, and coal products | 2.6 | 3.2 | 2.6 | 0.0 |
| Manufacture of nonmetallic mineral products | 1.4 | 1.3 | 1.2 | -0.2 |
| Manufacture of basic metals, metal products, and metal parts | 4.0 | 3.9 | 3.3 | -0.6 |
| Manufacture of machinery and transport equipment and parts | 5.4 | 5.9 | 4.3 | -1.1 |
| Electricity, gas, steam, water works, and water supply | 1.9 | 2.2 | 1.6 | -0.3 |
| Construction | 5.7 | 8.1 | 10.9 | 5.1 |
| Wholesale and retail trade-repair of motor vehicles and personal household | 7.1 | 8.2 | 11.2 | 4.2 |
| Hotels and restaurants | 1.7 | 1.8 | 2.7 | 1.0 |
| Transport and storage | 11.7 | 11.1 | 9.7 | -2.0 |
| Post and telecommunications | 1.1 | 1.1 | 1.7 | 0.6 |
| Financial intermediation | 3.0 | 3.8 | 3.5 | 0.5 |
| Real estate, renting | 0.7 | 0.1 | 0.3 | -0.4 |
| Computer and related activities/professional business activity | 0.2 | 1.4 | 2.9 | 2.7 |
| Public administration and defense | 18.9 | 17.0 | 12.2 | -6.6 |
| Education and R&D | 5.1 | 4.7 | 5.8 | 0.7 |
| Health, social work | 2.0 | 1.6 | 2.0 | -0.1 |
| Sanitation related activities | 0.5 | 0.5 | 0.2 | -0.3 |
| Other social activity | 3.3 | 3.9 | 3.3 | 0.1 |

Notes: Wage workers include regular salaried and casual labor. Self-employed are excluded.

the Pay Commissions. The logic adopted by the Pay Commission is generally to maintain the ratio between minimum pay scale and per capita income.

Table 2 presents the descriptive statistics of the sample used, and broad measures of wage inequality (like the standard deviation and the 90–10 gap in log wage). A strong pattern of results emerge from simple comparisons of measures of wage inequality. During the 1980s, earnings inequality in the urban labor market rose throughout the wage distribution, although the rate of increase was higher in upper tail. During 1983–93, the male 90/50 log earnings ratio rose by 18 log points and the 50/10 earnings ratio rose by 10 log points. This simultaneous expansion of upper and lower-tail inequality gave way to a significant divergence thereafter in the 1990s. All the increase in male 90–10 earnings inequality between 1993 and 2004 is accounted for by the rise in the 90–50 wage gap, 50–10 wage gap in fact contributed to reducing inequality as it declined by 14 log points. The trends are consistent with Kijima (2006), who also finds that the increase in wage inequality during 1983–99 has been mainly due to increases in the income of groups above the median. Banerjee and Piketty (2003), using individual tax return data from 1956 to 2000, also find that the income share of the top percentiles increased during the 1980s and 1990s. The share of Scheduled Castes has increased gradually in work force, while the share of public sector workers has reduced between 1993 and 2004, which is consistent with the fact that role of public sector declined during the 1990s. Similarly, the share of post secondary workers increased in the work force, although the increase in share was more in the 1980s compared to 1990s.

Table 3 presents the shares of different industries in wage employment. Between 1983 and 2004 the employment share of public administration and defense decreased from 19% to 12%, and most of the decrease happened between 1993 and 2004. This reinforces the trend of declining public sector employment after the 1990s reported in Table 1. The share

of wholesale and retail trade, utilities, and computer related activity increased between 1983 and 2004.

Figure 1 plots the kernel density of the log of real weekly wages for 3 years. During 1983–93, the whole distribution shifted to the right; however, between 1993 and 2004 the right part of distribution shifted to right while the left part remained virtually unchanged from 1993. The 1983 earning distribution is characterized by a higher density at mode and a lower dispersion. The dispersion has increased in the 1993 and 2004 distribution. There are evidences of bi-modality evolving in the earning distribution in the 1990s, which suggest polarization of wages taking place in India. However, we leave a closer examination of polarization for the future work.

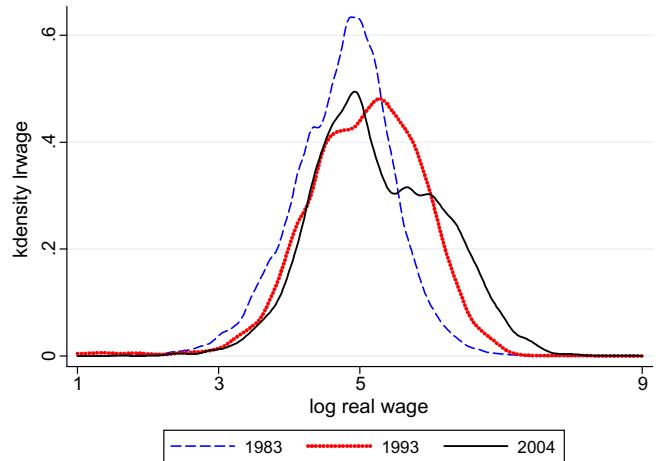


Figure 1. *Kernel density of log real wage*. Note: Gaussian kernel is used. The chosen width is the width that would minimize the mean integrated squared error.

4. RESULTS

(a) Quantile regression

Figures 2a and 3a plot the coefficient estimates, $\beta_t(\theta_i)$ for $\theta \in (0, 1)$, for education levels and demographic characteristics, respectively.¹⁷ The associated 95% confidence bands are represented by the dots. For each variable, the plots provide information on the coefficient estimates for 1983 (Panel A), 1993 (Panel B), and 2004 (Panel C). For comparison purposes, the coefficients estimated by mean regression (OLS) are reported as a dashed horizontal line. Figures 2b and 3b plot the change in estimated coefficient over time at each quantile for education levels and demographic characteristics, respectively. Panel A (left column) of Figures 2b and 3b plots the difference in coefficients during 1993–83, Panel B (middle column) plots the difference in coefficients between 2004 and 1993. We will investigate each variable's estimated effect on wages below.

(i) Returns to education

Figure 2a presents the returns to different levels of education. The intercept term represents the log wage distribution of the base group – primary educated regular salaried workers belonging to non Muslim, non SC/ST group and employed in the manufacturing of machinery and transport equipment industry residing in the state of Tamil Nadu. The wages of the base group workers increase with the quantile across the distribution in all 3 years: there is significant spread in wages for the base group workers. As expected, wages increase with the level of education, and this is across the whole distribution. In particular, a secondary or tertiary education increases the wage by a significant amount. While returns to lower education levels are uniform across the distribution compared to the base group; the returns to secondary and tertiary education are heterogeneous, and the heterogeneity has increased in 1993 and 2004.¹⁸ So while in 1983, secondary and tertiary education contributes more to between group inequality; their contribution to within group inequality strengthened in the 1990s (as returns become more heterogeneous).

Figure 2b presents the changes in returns to education over time. The intercept term shifted up in 1993 compared to 1983 (Panel A of Figure 2b). The base group workers are paid at an average approximately 30% more in real terms in 1993 compared to 1983. There is not much change in returns to different levels of education during 1983–93 compared to the base group. Hence, all workers seem to be paid higher real wages in 1993 than in 1983. The intercept term shifted up again in 2004 compared to 1993 (Panel B of Figure 2b). The base group workers are paid about 20% more on average in real terms in 2004 compared to what they were paid in 1993. The returns to tertiary education increased nearly by 18 percent across the entire distribution and returns to secondary education also increased at higher quantiles. The slower expansion of higher educated workers (see Table 1) may be one reason why returns to higher education went up much dramatically during the 1993–2004. Kijima (2006) also finds that the returns to primary and secondary education do not change much over time, while returns to tertiary education are stable up to 1993 and increase in 1999.¹⁹ However, our findings suggest that returns to secondary education also increased at the higher quantiles between 1993 and 2004. Thus, higher education is not only associated with higher wages but also wage distribution for secondary and tertiary educated workers has become more dispersed in the 1990s. Why are these results interesting? They suggest that the increase in level of education may increase

overall wage inequality because wages are more dispersed for the higher educated groups, even if the wage structure remains constant. However, prices paid to these groups in India did not remain constant – average returns to higher education increased contributing to further increase in wage inequality. Moreover, returns to tertiary education became more heterogeneous over time suggesting that wage inequality would have increased even if composition of work force and average returns to education levels had remained stable.

(ii) Demographic characteristics

In India, caste and religion also play an important role in wage determination. It is generally argued that “the caste system confines those from lower castes to a limited number of poorly paid, often socially stigmatized occupational niches from which there is little escape...” (Kabeer, 2002, p.3). Ethnicity is also often a source of exclusion – in India this translates into exclusion on the basis of religion and is largely applicable to the Indian Muslims (Das, 2003).

Figure 3a presents the effects of demographic variables on wages in all 3 years, while Figure 3b presents the changes in the effects of different demographic variables over 1993–1983 and 2004–1993. Our findings also suggest disadvantage for lower castes and Muslims. The SC/ST workers are paid less over the entire wage distribution in all 3 years (coefficients are negative). However, the gap does not seem to change as we move up the distribution. This implies although they are paid less, but wage distribution within these groups is not less dispersed than the excluded group. While the disadvantage faced by the SC workers did not change significantly during 1983–93, it increased significantly between 1993 and 2004 at the time when their share in the work force also expanded (Table 1). Although the disadvantage faced by SCs are well established in literature, the SCs enjoy positive discrimination in public sector jobs, and one of the possible reasons for increase in disadvantage may be decline of share of public sector employment. In contrast the ST workers did not experience much change in the disadvantage.²⁰ The case of Muslims is pretty interesting. They did not face any disadvantage in the 1983; however, disadvantage appeared in the 1993 and it increased between 1993 and 2004. Interestingly, the 1990s was a period which saw rise of Hindu-nationalist parties and increasing role of religion in Indian politics besides caste. The increasing disadvantage of Muslims in India is also documented in Government of India. (2006) report. Dutta (2006) also finds that belonging to the SC/ST or a Muslim group significantly decreases the wage received by regular workers in 1983, 1993, and 1999.

(iii) Industry effects

Most of the industry dummies are statistically significant in all 3 years. The point estimate of industry effects are presented in Table 4a (for 1993) and Table 4b (for 2004). The coefficients are displayed as deviations from the employment-weighted average industry effect, and industries are ranked according to the magnitude of industry's effect at the mean (given by OLS). The last row of Tables 4a and b refers to joint significance of industry effects. In these tests, the null is always rejected, and we conclude that the industry matters for the determination of wages.

In 2004, a positive wage premium - compared to the average industry - is paid by sectors that either include capital intensive industries (e.g., mining, electricity, manufacturing of machinery, petroleum) or skill-intensive industries (e.g., computer, financial intermediation), while a negative wage premium is paid by sectors that include less capital intensive industries

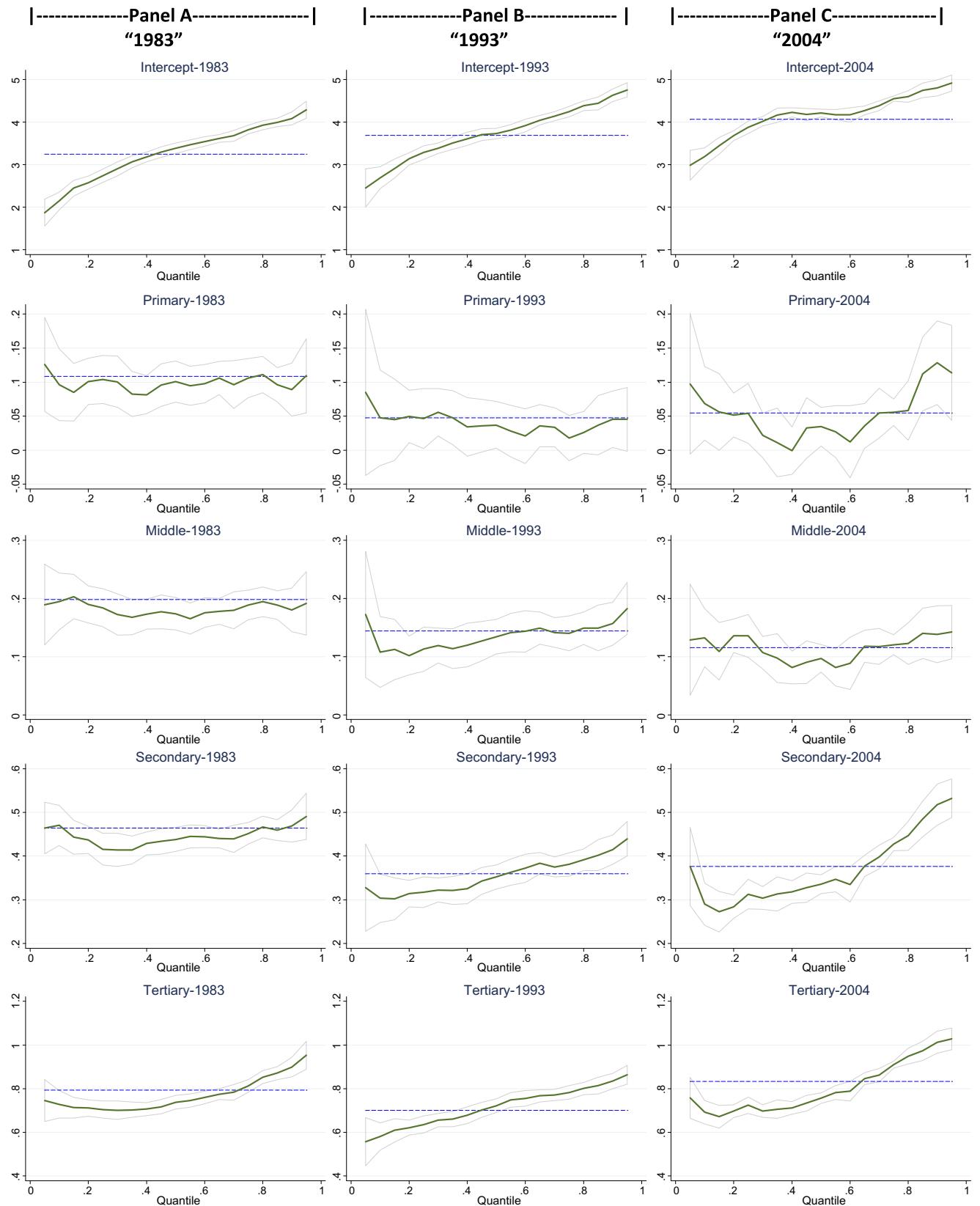


Figure 2a. Regression coefficients for different stages of education. Notes: (1) The coefficients refer to regular salaried workers. To get the estimates for casual workers, interactive terms of casual workers (reported in Appendix Tables 7–9) need to be added. (2) Regular salaried workers with education below primary are the excluded education group. (3) Dashed horizontal line refers to OLS estimate. (4) Y-axis scale differs for different levels of education.

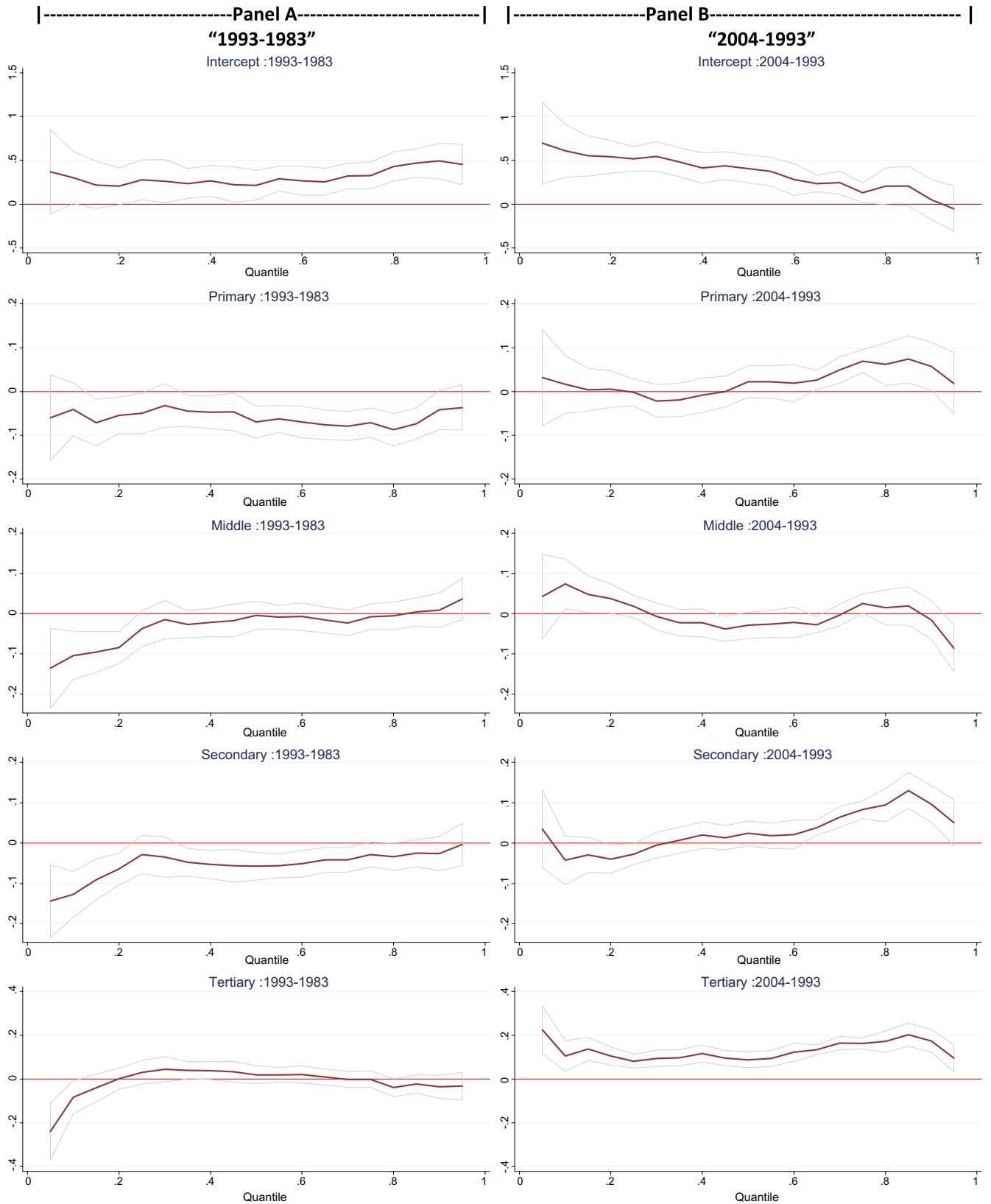


Figure 2b. Changes in regression coefficients of different levels of education. Note: Solid horizontal line refers to zero.

(e.g., light manufacturing such as the foodstuffs, tobacco, and textiles industries) or less skill-intensive industries (e.g., agriculture, hotel). These results are consistent with the findings

of studies on other countries in which industries that are capital-intensive or skill-intensive (or both) have higher wage premia (Dickens & Katz, 1987; Hasan & Chen, 2003).

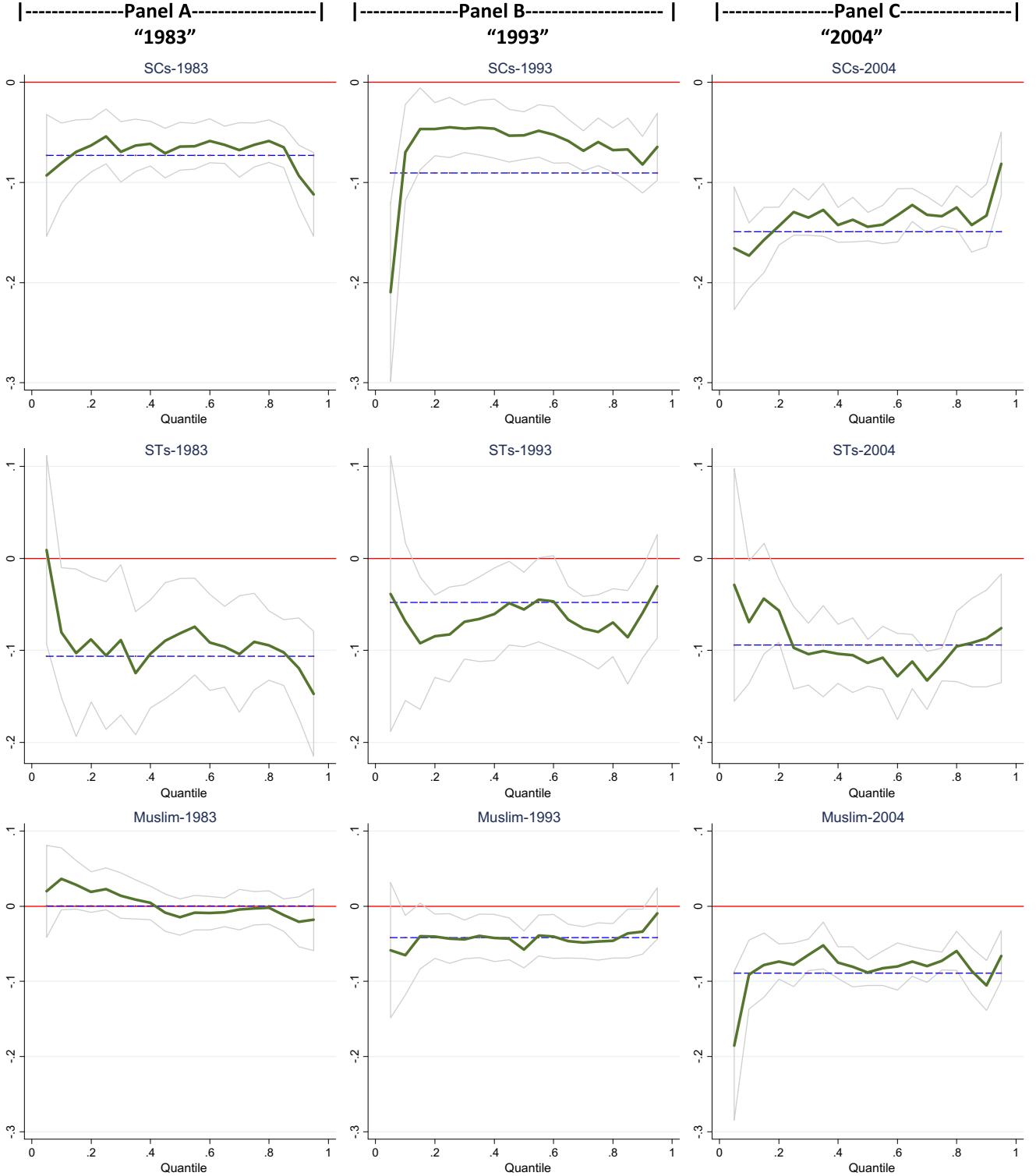


Figure 3a. Regression coefficients for demographic variables. Notes: (1) Solid horizontal line refers to zero. (2) Dashed horizontal line refers to OLS estimate. (3) Y-axis scale differs for different characteristics.

There are some interesting trends in industry premium, for example, computer and business activity, which paid negative wage premium compared to the average industry in 1993, paid a significant positive wage premium in 2004. Also, the premium became highly heterogeneous across quantiles suggesting that an expansion of computer industry will increase wage inequal-

ity. The textile industry paid a positive wage premium in 1993, but paid a significant negative wage premium in 2004. Similarly, post and telecommunication paid a significant wage premium over the average industry in 2004 versus a negative premium in 1993. Also, the premium became more heterogeneous. Interestingly, there has been a growing role of private sector in

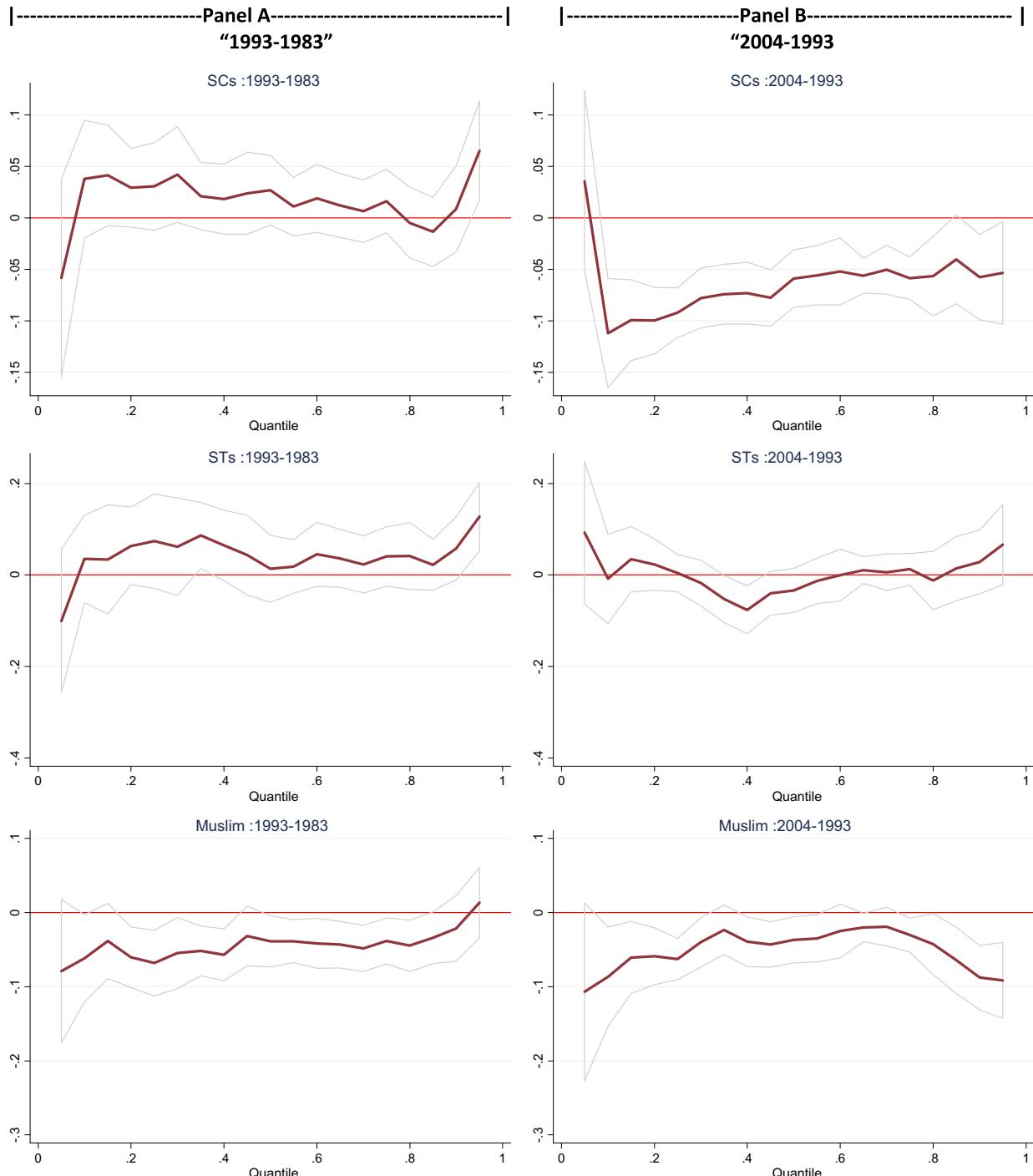


Figure 3b. *Changes in regression coefficients of demographic variables. Note: Solid horizontal line refers to zero.*

telecommunication in the 1990s. There is little evidence of increased heterogeneity in premium in the manufacturing industries between 1993 and 2004. However, heterogeneity increased in mining, computer, telecommunication, and electricity. Although, increasing heterogeneity in premium suggests increase in inequality, the share of these industries in total workforce remains low. For the industries which have larger shares in workforce, e.g., public administration, transport, construction, and wholesale trade, there is little evidence of increase in heterogeneity in industry premium.

Being employed in public sector pays a significant wage premium, and this wage premium has increased between 1993 and

2004 (Appendix Tables 8 and 9). More importantly, evidences suggest wage compression in the public sector: much higher wage premium at the lower quantiles compared to wage premium at the higher quantiles. The wage premium enjoyed by public sector is not surprising as in most cases the public sector wants to be a good employer and may be willing to pay higher wages to its employees. As a good employer the public sector may be willing to pay lower-skilled workers more. However, what is surprising is that the private sector in India is thriving in recent past and there is a growing perception that growth in wages for public sector employees has lagged behind the growth of wages for private sector employees, especially for

Table 4a. *Industry effects, 1993–94*

| Regression method | (1) | (2) | (3) | (4) | (5) | (6) |
|--|--------|--------|--------|--------|--------|--------|
| | OLS | Q 10 | Q 25 | Q 50 | Q 75 | Q 90 |
| | QR | QR | QR | QR | QR | QR |
| Mining and quarrying | 0.25 | 0.22 | 0.23 | 0.27 | 0.28 | 0.31 |
| Financial intermediation | 0.23 | 0.13 | 0.22 | 0.27 | 0.27 | 0.27 |
| Electricity, gas, steam, water works, and water supply | 0.21 | 0.18 | 0.13 | 0.19 | 0.16 | 0.21 |
| Manufacture of machinery and transport equipment and parts | 0.18 | 0.22 | 0.15 | 0.13 | 0.16 | 0.20 |
| Manufacture of nonmetallic mineral products | 0.14 | 0.14 | 0.03 | 0.06 | 0.13 | 0.13 |
| Manufacture of chemicals, rubber, plastic, petroleum, and coal products | 0.12 | 0.19 | 0.08 | 0.08 | 0.11 | 0.15 |
| Manufacture of basic metals, metal products, and metal parts | 0.08 | 0.14 | 0.07 | 0.02 | 0.04 | 0.09 |
| Manufacture of textiles, leather, fur, wearing apparel, and footwear | 0.06 | 0.11 | 0.09 | 0.04 | 0.00 | 0.00 |
| Manufacture of wood and wood products | 0.06 | 0.10 | 0.02 | -0.05 | 0.04 | 0.08 |
| Transport and storage | 0.05 | 0.06 | 0.02 | 0.04 | 0.03 | 0.03 |
| Public administration and defense | 0.03 | 0.03 | 0.05 | 0.05 | 0.04 | 0.01 |
| Sanitation related activities | 0.03 | -0.05 | -0.08 | 0.01 | -0.04 | -0.07 |
| Construction | 0.02 | -0.03 | 0.05 | 0.07 | 0.06 | 0.04 |
| Health, social work | 0.02 | 0.01 | -0.01 | -0.02 | 0.03 | 0.01 |
| Education and R&D | -0.01 | -0.13 | 0.02 | 0.04 | 0.01 | -0.06 |
| Manufacture of paper, paper products, printing, and publishing | -0.03 | 0.06 | -0.08 | 0.02 | 0.02 | -0.07 |
| Post and telecommunications | -0.03 | -0.03 | 0.00 | 0.03 | 0.03 | -0.03 |
| Computer and related activities/professional business activity | -0.08 | -0.09 | -0.10 | -0.09 | -0.11 | -0.03 |
| Real estate, renting | -0.10 | 0.11 | -0.24 | -0.12 | -0.16 | -0.38 |
| Hotels and restaurants | -0.11 | -0.03 | -0.03 | -0.11 | -0.11 | -0.09 |
| Manufacture of food, beverage, and tobacco products | -0.15 | -0.20 | -0.16 | -0.13 | -0.16 | -0.09 |
| Wholesale and retail trade-repair of motor vehicles and personal household | -0.24 | -0.21 | -0.25 | -0.25 | -0.23 | -0.19 |
| Other social activity | -0.26 | -0.25 | -0.22 | -0.23 | -0.24 | -0.22 |
| Agriculture, hunting, forestry, and fishing | -0.32 | -0.34 | -0.32 | -0.33 | -0.32 | -0.33 |
| Joint significance of industry effects (<i>p</i> - values) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

Notes: (1) The coefficients are expressed as deviation from employment weighted average industry effect. (2) Industries are ranked according to the magnitude of industry effects at the mean (given by OLS).

Table 4b. *Industry effects, 2004–05*

| Regression method | (1) | (2) | (3) | (4) | (5) | (6) |
|--|--------|--------|--------|--------|--------|--------|
| | OLS | Q 10 | Q 25 | Q 50 | Q 75 | Q 90 |
| | QR | QR | QR | QR | QR | QR |
| Mining and quarrying | 0.47 | 0.33 | 0.42 | 0.45 | 0.53 | 0.51 |
| Computer and related activities/professional business activity | 0.28 | 0.09 | 0.13 | 0.24 | 0.41 | 0.57 |
| Financial intermediation | 0.26 | 0.20 | 0.28 | 0.27 | 0.25 | 0.28 |
| Electricity, gas, steam, water works, and water supply | 0.25 | 0.16 | 0.22 | 0.20 | 0.25 | 0.34 |
| Manufacture of chemicals, rubber, plastic, petroleum, and coal products | 0.20 | 0.22 | 0.17 | 0.15 | 0.18 | 0.24 |
| Manufacture of machinery and transport equipment and parts | 0.19 | 0.18 | 0.15 | 0.15 | 0.19 | 0.23 |
| Post and telecommunications | 0.12 | -0.02 | 0.09 | 0.12 | 0.14 | 0.30 |
| Manufacture of wood and wood products | 0.07 | 0.09 | 0.08 | 0.06 | 0.05 | 0.07 |
| Transport and storage | 0.07 | 0.08 | 0.09 | 0.09 | 0.08 | 0.05 |
| Manufacture of basic metals, metal products, and metal parts | 0.03 | 0.08 | 0.04 | 0.01 | 0.03 | 0.08 |
| Manufacture of nonmetallic mineral products | 0.03 | 0.03 | 0.06 | -0.01 | -0.06 | 0.01 |
| Construction | 0.02 | 0.05 | 0.03 | 0.02 | 0.02 | 0.01 |
| Sanitation related activities | 0.00 | -0.37 | 0.09 | -0.06 | 0.18 | 0.18 |
| Public administration and defense | -0.01 | -0.07 | -0.04 | -0.01 | 0.00 | 0.01 |
| Health, social work | -0.01 | -0.07 | -0.22 | -0.08 | 0.10 | 0.10 |
| Education and R&D | -0.02 | -0.12 | -0.02 | 0.03 | 0.02 | -0.03 |
| Manufacture of textiles, leather, fur, wearing apparel, and footwear | -0.06 | 0.07 | 0.02 | -0.06 | -0.15 | -0.20 |
| Manufacture of paper, paper products, printing, and publishing | -0.06 | 0.03 | -0.01 | -0.03 | -0.05 | -0.09 |
| Hotels and restaurants | -0.07 | -0.03 | -0.05 | -0.04 | -0.12 | -0.14 |
| Other social activity | -0.17 | -0.14 | -0.12 | -0.18 | -0.19 | -0.17 |
| Manufacture of food, beverage, and tobacco products | -0.19 | -0.13 | -0.18 | -0.18 | -0.19 | -0.25 |
| Wholesale and retail trade-repair of motor vehicles and personal household | -0.21 | -0.17 | -0.19 | -0.20 | -0.22 | -0.24 |
| Real estate, renting | -0.31 | -0.34 | -0.64 | -0.14 | -0.04 | -0.30 |
| Agriculture, hunting, forestry, and fishing | -0.39 | -0.30 | -0.39 | -0.40 | -0.42 | -0.41 |
| Joint significance of industry effects (<i>p</i> - values) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

Notes: (1) The coefficients are expressed as deviation from employment weighted average industry effect. (2) Industries are ranked according to the magnitude of industry effects at the mean (given by OLS).

high skilled people. This perception do not find support, and in fact points in the opposite way as the premium enjoyed by the public sector has increased during the 1990s. The public sector workers at the top end not only enjoy a positive premium but the premium has increased between 1993 and 2004. The share of public-employment in total workforce declined from 32% to 27%. The decline in public sector employment may contribute to increased inequality as public sector reduces inequality by compressing the wages.

The marginal effects discussed heretofore vary across quantiles and over time. In addition, covariate distributions have changed over time (Table 2). To summarize the effects of changes in covariates and change in returns to the covariates on the overall change in wage distribution, we now turn to the MM (2005) decomposition.

(b) Decomposition of changes in wage distribution

Figures 4a and b present the decomposition of wage differences during 1993–83, and between 2004 and 1993, respectively, for quantile 5–95 with 95% confidence intervals. The confidence bounds are the 2.5% and 97.5% quantiles of the bootstrap distribution of the relevant statistic obtained by bootstrap with 1000 replications. Table 5 reports the results of the Oaxaca-Blinder and MM decompositions at select quantiles.

(i) Wage changes during 1983–93

The Oaxaca-Blinder decomposition shows that real wages increased by 28 log points during 1983–93, with the change in covariates explaining 5 log points and the change in coefficients explaining 23 log points. However, once we move beyond average, we find that real wages increased by 18 log points at the 10th percentile, 30 log points at the median, and 47 log points at the 90th percentile. Thus, increase in wages is heterogeneous across quantiles, with the increase being larger at the higher quantiles. This unequal wage growth led to increase in wage inequality in a period where the real wages have been growing throughout the distribution. Hence, the increase in wage inequality in this period is distributed over the entire wage distribution. In the presence of such heterogeneity in the increase in real wages, the Oaxaca-Blinder may hide important information.

The MM decomposition captures the heterogeneity in the covariate and the coefficient effects (Figure 4a): both are larger at higher quantiles. Change in both the covariates and the coefficients contributes to the actual evolution of real wages, and

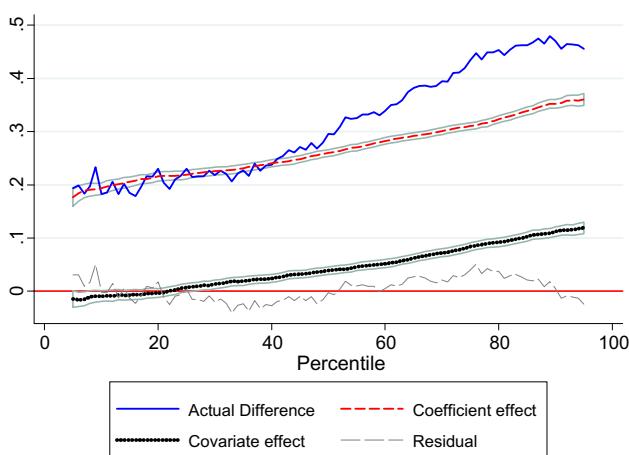


Figure 4a. Decomposition of difference in wages during 1983–93.

their effect is significantly different from zero (the confidence intervals do not include zero) at all of the estimated quantiles. However, the coefficient effect is quantitatively more important than the covariate effect at each of the estimated quantiles. Overall, the models work fairly well, as the residuals account for a relatively small part of the total change. The increase in the 90–10 gap in log wages is evenly distributed between changing composition (43% of total change) and changing prices (55% of total change). Similarly, both coefficient and covariate effect contributed in increase in upper and lower tail inequality, and the coefficient effect has been quantitatively more important than the covariate effect.

(ii) Wage changes between 1993 and 2004

The Oaxaca-Blinder decomposition shows that real wages increased by 22 log points between 1993 and 2004, and the change in the coefficients explains 23 log points, while the change in the covariates explains –1 log points. However, once we move beyond mean, we find that the growth of real wages between 1993 and 2004 has not only been heterogeneous but also has very different trend compared with growth of real wages during 1983–93. Between 1993 and 2004, workers in the middle of the distribution experienced very small increase in their real wages, while workers at lower end of the distribution experience some increase in real wages. In upper half of the distribution (above median) the rate of increase is higher at the higher quantiles. More, importantly, the increase at the top end of the distribution is much higher compared to the increase at lower or middle end of the distribution, and thus contributing to expansion of overall and upper tail inequality. Higher wage growth at the lower and top quantiles compared to middle quantiles suggests a polarization taking place in the wage distribution. These trends are similar to trends observed in

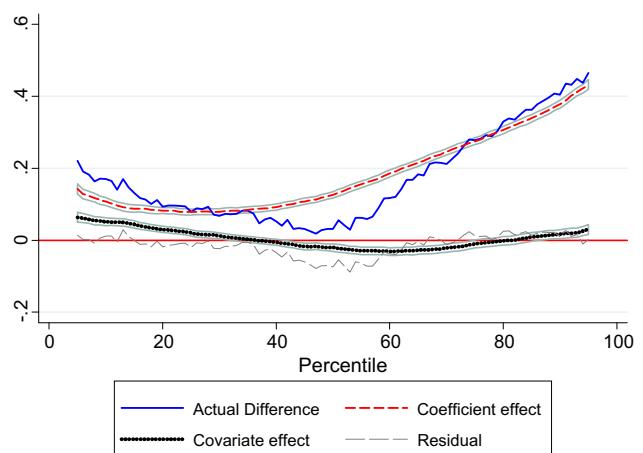


Figure 4b. Decomposition of difference in wages during 2004–1993. Notes: (1) Actual difference is the difference of actual empirical densities of year 1 from year 0 at each quantile, i.e., $\alpha\{f(w(1))\} - \alpha\{f(w(0))\}$. Year 1 refers the current year and year 0 refers previous year. (2) Residual is the difference of difference in actual empirical densities and difference in fitted densities at each quantile, i.e., $\{\alpha(f(w(1))) - \alpha(f(w(0)))\} - \{\alpha(f^*(w(1))) - \alpha(f^*(w(0)))\}$. (3) Coefficient effect is difference between the counterfactual density (with prices of year 1 and covariates of year 0) and the fitted density for year 0, i.e., $\alpha\{f^*(w(1); x(0))\} - \alpha\{f^*(w(0))\}$. (4) Covariate effect is difference of fitted density of year 1 and counterfactual density (with prices of year 1 and covariates of year zero), i.e., $\alpha\{f(w(1))\} - \alpha\{f^*(w(1); x(0))\}$. (5) The shaded area around coefficient and covariate effect refers to 95% confidence interval. The confidence bounds are the quantiles 2.5% and 97.5% of the distribution of the relevant statistic obtained by bootstrap with 1,000 replications. See text for further details.

Table 5. Decomposition of wage changes over time

| Percentile | Marginal-1 | Marginal-0 | Observed difference | Coefficient effect | Covariate effect | Residual |
|--|------------|------------|---------------------|-----------------------|--------------------------|----------|
| <i>Wage differential during 1993–83</i> | | | | | | |
| | 1993 | 1983 | | | | |
| Mean * | 5.038 | 4.759 | 0.279 | 0.228 | 0.051 | 0.000 |
| 10th | 4.017 | 3.835 | 0.182 | 0.194 0.182; 0.203 | -0.010 -0.019; 0.001 | -0.002 |
| 25th | 4.537 | 4.307 | 0.230 | 0.219 0.211; 0.227 | 0.007 -0.001; 0.015 | 0.004 |
| 50th | 5.110 | 4.814 | 0.296 | 0.260 0.253; 0.266 | 0.039 0.031; 0.046 | -0.003 |
| 75th | 5.647 | 5.213 | 0.434 | 0.310 0.304; 0.317 | 0.084 0.076; 0.098 | 0.040 |
| 90th | 6.064 | 5.594 | 0.471 | 0.352 0.344; 0.361 | 0.112 0.103; 0.121 | 0.006 |
| 90th–10th | 2.047 | 1.759 | 0.288 | 0.159 | 0.122 | 0.008 |
| 90th–50th | 0.954 | 0.780 | 0.175 | 0.093 | 0.073 | 0.008 |
| 50th–10th | 1.093 | 0.979 | 0.114 | 0.066 | 0.049 | -0.001 |
| <i>Wage differential between 2004 and 1993</i> | | | | | | |
| | 2004 | 1993 | | | | |
| Mean * | 5.258 | 5.037 | 0.220 | 0.230 | -0.010 | 0.000 |
| 10th | 4.187 | 4.017 | 0.170 | 0.107 0.097; 0.118 | 0.051 0.041; 0.062 | 0.012 |
| 25th | 4.616 | 4.537 | 0.079 | 0.079 0.070; 0.087 | 0.021 0.012; 0.029 | -0.020 |
| 50th | 5.142 | 5.110 | 0.032 | 0.126 0.117; 0.135 | -0.020 -0.031; -0.010 | -0.074 |
| 75th | 5.925 | 5.647 | 0.278 | 0.275 0.265; 0.285 | -0.010 -0.022; 0.001 | 0.013 |
| 90th | 6.469 | 6.064 | 0.405 | 0.378 0.367; 0.389 | 0.017 0.004; 0.029 | 0.010 |
| 90th–10th | 2.282 | 2.047 | 0.234 | 0.271 | -0.034 | -0.002 |
| 90th–50th | 1.327 | 0.954 | 0.373 | 0.252 | 0.037 | 0.084 |
| 50th–10th | 0.954 | 1.093 | -0.139 | 0.018 | -0.071 | -0.086 |

Notes: (1) * Oaxaca-Blinder decomposition. (2) The second entry is 95% confidence interval for the change. The confidence bounds are the quantiles 2.5% and 97.5% of the distribution of the relevant statistic obtained by bootstrap with 1000 replications. (3) Marginal-1 and Marginal-0 refers observed marginal wage distributions in year 1 and year 0. (4) Observed difference is the difference between observed marginal distributions of year 1 and year 0 at each quantile, i.e., $\alpha\{f(w(1))\} - \alpha\{f(w(0))\}$. Year 1 refers to the current year and year 0 refers to previous year. (5) Coefficient effect is difference between the counterfactual density (with prices of year 1 and covariates of year 0) and the fitted density for year 0, i.e., $\alpha\{f^*(w(1); x(0))\} - \alpha\{f^*(w(0))\}$. (6) Covariate effect is difference between fitted density of year 1 and counterfactual density with prices of year 1 and covariates of year zero, i.e., $\alpha\{f^*(w(1))\} - \alpha\{f^*(w(1); x(0))\}$. (7) Residual is the difference of difference in actual empirical densities and difference in fitted densities at each quantile, i.e., $\{\alpha\{f(w(1))\} - \alpha\{f(w(0))\}\} - \{\alpha\{f^*(w(1))\} - \alpha\{f^*(w(0))\}\}$. See text for further details.

the US. Autor, Katz, and Kearney (2006) provide evidence of polarization of wages in the US during the 1990s such that wage inequality only continued to rise in the upper part of the distribution.

Figure 4b presents the MM decomposition results. Unlike the 1980s, the changes in composition of workforce have not contributed to increase in real wages, and most of the increase in real wages are driven by increase in prices, i.e., coefficient effect which is not only positive throughout the distribution but also larger at the higher quantiles (after median). The increase in prices explains majority of increase in upper tail inequality (90–50 gap), while the increase in prices marginally increases lower tail inequality; however the changing composition at the lower end of the distribution reduces inequality, and as a result the lower tail inequality declined.

Why the composition effect negative? The share of higher educated workers did not increase as much in 1990s as it did in the 1980s. The share of public sector, which paid a significant premium, declined significantly during the 1990s. The share of SC and Muslim workers increased between 1993 and 2004, and both of these groups face a significant disadvantage which increased during the 1990s. Similarly, the textile industry which employed a significant amount of workforce

started paying significant negative premium in the 2004 whereas it was paying a significant positive premium in the 1993. All of these factors may have contributed to the negative composition effect.

Our findings pertaining to the increase in wage differentials in 1990s is consistent with Kijima (2006) who also finds that increases in observed skill prices account for a dominant part of the increase in wage differentials (e.g., the 90th–50th gap) during 1993–99. However, our results for the 1980s do not accord with the findings of Kijima (2006). Kijima (2006) finds that changes in the observed covariates played a dominant role in the increase in wage differentials during 1983–87, and during 1987–93. The differences in findings may arise for two reasons. First, the JMP decomposition, used by Kijima (2006), uses OLS coefficients in the decomposition which does not allow for heterogeneity in the coefficients across the distribution. Second, the sample used in Kijima (2006) differs from the sample used in this paper. While our sample contains only wage employed, Kijima (2006) also include self-employed workers besides the wage employed. As wages are not reported for self employed workers, Kijima (2006) used predicted wages for self-employed workers using OLS coefficients from wage employed workers (for whom wages

Table 6. JMP decomposition of wage changes

| | Total change | Observed quantities | Observed prices | Unobservable |
|--|--------------|---------------------|-----------------|--------------|
| <i>Panel I: Wage differential during 1993–83</i> | | | | |
| 10th | 0.182 | −0.002 | 0.261 | −0.077 |
| 25th | 0.230 | −0.051 | 0.275 | 0.005 |
| 50th | 0.296 | −0.043 | 0.301 | 0.038 |
| 75th | 0.433 | 0.007 | 0.321 | 0.106 |
| 90th | 0.469 | 0.018 | 0.321 | 0.130 |
| 90th–10th | 0.287 | 0.020 | 0.060 | 0.207 |
| 90th–50th | 0.173 | 0.061 | 0.020 | 0.092 |
| 50th–10th | 0.114 | −0.041 | 0.040 | 0.114 |
| <i>Panel II: Wage differential between 2004 and 1993</i> | | | | |
| 10th | 0.170 | 0.053 | 0.149 | −0.031 |
| 25th | 0.079 | −0.001 | 0.156 | −0.076 |
| 50th | 0.032 | −0.119 | 0.217 | −0.066 |
| 75th | 0.278 | −0.036 | 0.360 | −0.046 |
| 90th | 0.405 | 0.000 | 0.395 | 0.010 |
| 90th–10th | 0.234 | −0.053 | 0.246 | 0.041 |
| 90th–50th | 0.373 | 0.119 | 0.178 | 0.076 |
| 50th–10th | −0.139 | −0.172 | 0.068 | −0.035 |

Note: JMP refers to Juhn, Murphy and Pierce (1993).

are reported) assuming that the same earning function will hold for the self-employed also.

To see why differences in the results arise, we also perform the JMP decomposition on our sample. The results are presented in Table 6. During 1983–93, the increase in returns dominates the changes in the covariates at the select quantiles reported. This is very much in conformity with our Oaxaca–Blinder and MM decompositions. However, the differences in the results arise once we compute the reasons for increase in wage differentials (e.g., the 90th–50th, the 50th–10th, and the 90th–50th gap as reported by Kijima (2006)). Since the JMP decomposition does not capture the heterogeneity in the coefficient effect, it understates the role of the coefficient effect in the increase in wage differentials. The MM decomposition captures the heterogeneity in the coefficient effect because of use of quantile regression in place OLS. Hence we believe that the coefficient effect played an important role in the increase in wage differentials in the 1980s also.

5. CONCLUSION

Indian economy has been among the fastest growing economies in the developing world since the 1980s. However, the higher growth rate during the past two decades has also been associated with an increase in wage inequality. While wage inequality in India is well studied, all such studies (to our knowledge) focus on averages, relying mostly on OLS estimates. We find that such a narrow focus does not depict the complete picture in a heterogeneous society as India. We find that real wages increased across the entire wage distribution during 1983–93 and the increase was larger at the higher quantiles. However, between 1993 and 2004, the male workers at the bottom and top end of the distribution experienced a larger increase in wages compared to workers in the middle part

of the distribution. The increase in real wages was lower as we move from bottom end of the distribution toward median; however, the increase was larger as we move from middle part of the distribution toward top end of the distribution. As a result, while both lower and upper tail inequality increased in the 1980s, in the 1990s, upper tail inequality expanded while lower tail inequality contracted. However, the overall inequality increased in the 1990s as the increase in upper tail inequality was much larger than the decrease in lower tail inequality.

Further decomposing the changes in wages, we find that the increase in real wage over the last two decades is driven mostly by the increase in prices paid. During 1983–93, both the coefficient and the covariate effects contributed to increase in wages, though the coefficient effect was more important than the covariate effect. However, between 1993 and 2004, the contribution of the covariate effect was either negative or negligible while almost all of the increase in wages has been due to the positive coefficient effect.

Our findings also suggest that returns of many characteristics are heterogeneous and the least squares method fails to capture this heterogeneity. The returns to higher education (secondary and tertiary) both increased in the 1990s. In addition, the returns also have become more heterogeneous across the distribution in the 1990s: larger returns at the higher quantiles. The findings of the paper suggest that wage inequality in urban India is not likely to decrease and in fact will probably increase further in the near future as the share of higher educated especially tertiary educated workers in the workforce increases. However, in long run, increases in the skill premium are expected to stimulate further increases in human capital investment (Topel, 1999), and increases in the number of college graduates may decrease the wage inequality in the long run as South Korea experienced in the 1970s and 1980s (Kim & Topel, 1995).

NOTES

1. An exception is Kijima (2006) which decomposes the changes in the 90th–10th, 90th–50th, and 50th–10th percentile of log wage differential.
2. The evidence for this comes from a number of different countries such as the USA (Buchinsky, 1994), Germany (Fitzenberger & Kurz, 2003), Uruguay (González & Miles, 2001), Zambia (Nielsen & Roshholm, 2001), and Portugal (Machado & Mata, 2001).

3. Leibbrandt, Levinsohn, and McCrary (2005) proposes a simple extension to DiNardo et al. (1996) to separate the role of quantities and prices in influencing the shape of the wage distribution.
4. MM (2005) draws θ_i from a uniform distribution and then estimate quantile regressions at those selected quantiles; however, Albrecht, Vuuren, and Vroman (2009) find this approach removes the sampling error involved in the first step as proposed in Machado and Mata (2005).
5. To take into account the household survey weights, we implemented unequal probability sampling with replacement. We end up with 999,000 observations for w^* .
6. There is another possible counterfactual that can be used in the decomposition, i.e., $f^*(w(0); x(1))$, which is the wage density that would have prevailed if all covariates are distributed as in year 1, but workers are paid as in year 0. However, qualitatively our results are invariant to the alternative counterfactual, i.e., $f^*(w(0); x(1))$.
7. The residual term comprises the simulation errors which disappears with more simulations, the sampling errors which disappears with more observations and the specification error induced by estimating linear quantile regression (Melly, 2005).
8. NSSO conducts thick round surveys (called “quinquennial rounds”) at 5-year intervals. The data before 1983 are not available and 2004–05 are the most recent round available. We chose to use 1993–94 data as they divide the past 20 years into two equally spaced time periods. India’s decision to liberalize in May 1991 was sudden and externally imposed. One would expect that this sudden policy shift will affect the labor market with significant lag. So 1993–94 serves as a possible benchmark for end of closed economy era and start of an open economy era.
9. A regular wage salaried worker is a person who works in others’ farm or nonfarm enterprises (household and nonhousehold) and in return received salary or wages on a regular basis; while a casual worker is a person who is engaged in others’ farm or non-farm enterprises (household and nonhousehold) and in return, received wages according to the terms of the daily or periodic work contract.
10. Dutta (2006) finds that while the explanatory power of human capital variables is reasonably high for regular wage/salaried workers, that for casual workers is very low, suggesting that human capital characteristics do not explain the wage determination process for casual labor.
11. Kijima (2006) include self-employed in her sample, and predicts the earnings of self-employed based on Mincerian equations estimated from the sample of wage/salaried workers. Not only does this assume that the relationship between observable characteristics and earnings are identical across wage/salaried workers and the self-employed, it also assumes that this relationship fully explains earnings of self-employed. In addition, it imposes homogeneous returns for self-employed workers thus understating the role of prices in increase in wage inequality.
12. Female labor force participation remains quite low in India. In 2004, Labor force participation rate (LFPR) for urban female in age group 21–60 was 24% compared to 93% for the urban male in the same age group. In the absence of good exclusion variables in the data set, we could not correct for sample selection.
13. Buchinsky (1998) suggests a way to correct sample selection, and this selection correction is incorporated into the MM technique by Albrecht et al. (2009). However, Buchinsky’s selection correction technique requires a valid exclusion variable. Possible exclusion variables available in our data are household structure variables (i.e., number of children, or the dependency ratio, etc.) and landholding. Landholding may be a good exclusion variable in rural areas, but in urban areas it is not very useful. Similarly, household structure variables are suspect since how they affect the employment participation of the male working population is not very clear.
14. The information about public sector employment is not available in the 1983 data. Hence, public sector dummy is not included in the decomposition (and coefficient changes analysis) of wages during 1983–93; however, it is included in the decomposition (and coefficient changes analysis) between 1993 and 2004.
15. Illiterates/below primary is treated as base dummy for education levels. Dummies included represent primary, middle, secondary, and tertiary levels of education.
16. Muslims constitute 13.4% of the total population in 2001. A committee constituted by Government of India (popularly known as “Sachar Committee”, 2006), to study the “social, economic and educational status of Muslims in India”, points out that by and large, Muslims rank somewhat above the SCs/STs but below Hindu other backward castes, Hindu upper castes, or other Minorities in almost all indicators considered.
17. Figure 2a refers to returns for regular workers. To derive the returns for casual workers, one need to add the coefficients of interactions of casual labor reported in the Appendix Tables.
18. Note that the approximately uniform returns are with respect to base group workers whose wage distribution is heterogeneous. The least squares miss the heterogeneity that comes through the wage distribution of base group as well as heterogeneity in returns to individual education levels compared with the base group.
19. In Kijima (2006), primary level combines both primary and middle education levels.
20. Most of the previous studies combine the SCs and the STs together. However, while the exclusion and deprivation of the SCs is closely associated with institution of caste and untouchability, the STs isolation and exclusion however, is not related to caste or religion, but is based on their ethnic identity. Historically, the STs have been different from the mainland Indian society with a distinct culture, language, social organization, and economy practicing.

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APPENDIX A

See Appendix Tables 7–9.

Table 7. OLS and quantile regression, 1983

| Regression method | (1) OLS | (2) Q 10 QR | (3) Q 25 QR | (4) Q 50 QR | (5) Q 75 QR | (6) Q 90 QR |
|---|------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Education level (excluded group: below primary) | | | | | | |
| Primary school | 0.109*** | 0.096*** | 0.104*** | 0.101*** | 0.106*** | 0.089*** |
| Middle school | 0.198*** | 0.195*** | 0.184*** | 0.174*** | 0.189*** | 0.180*** |
| Secondary school | 0.464*** | 0.470*** | 0.416*** | 0.438*** | 0.452*** | 0.469*** |
| Tertiary graduate | 0.794*** | 0.729*** | 0.704*** | 0.738*** | 0.812*** | 0.899*** |
| Age | 0.052*** | 0.072*** | 0.063*** | 0.048*** | 0.041*** | 0.040*** |
| Age squared | -0.050*** | -0.078*** | -0.064*** | -0.045*** | -0.035*** | -0.031*** |
| Scheduled castes | -0.073*** | -0.081*** | -0.054*** | -0.064*** | -0.063*** | -0.093*** |
| Scheduled castes | -0.106*** | -0.080** | -0.106*** | -0.081*** | -0.091*** | -0.119*** |
| Muslim | 0.001 | 0.036* | 0.023 | -0.014 | -0.003 | -0.021 |
| Married | 0.134*** | 0.177*** | 0.158*** | 0.130*** | 0.081*** | 0.079*** |
| Casual worker | -0.349*** | -0.457*** | -0.398*** | -0.370*** | -0.319*** | -0.268*** |
| Casual worker * Primary educated | 0.034 | 0.085* | 0.046 | 0.017 | 0.015 | 0.045 |
| Casual worker * Middle educated | -0.030 | 0.047 | -0.023 | -0.030 | -0.038 | -0.069* |
| Casual worker * Secondary educated | -0.184*** | -0.182*** | -0.192*** | -0.167*** | -0.084** | -0.181*** |
| Casual worker * Tertiary educated | -0.410*** | -0.505*** | -0.271** | -0.435*** | -0.527*** | -0.518*** |
| Employed in public sector | NA | NA | NA | NA | NA | NA |
| Constant | 3.243*** | 2.147*** | 2.738*** | 3.385*** | 3.824*** | 4.086*** |
| Control for industry (23 industry dummies) | Yes | Yes | Yes | Yes | Yes | Yes |
| Control for states | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 25,489 | 25,489 | 25,489 | 25,489 | 25,489 | 25,489 |
| R-squared | 0.478 | | | | | |

Notes: The information about public sector employment is not available in 1983 data. Because of some missing information on wages, the number of observations in the regression is less than the number of observations reported in Table 2.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

Table 8. OLS and quantile regression, 1993–94

| Regression method | (1) OLS | (2) Q 10 QR | (3) Q 25 QR | (4) Q 50 QR | (5) Q 75 QR | (6) Q 90 QR |
|---|------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Education level (excluded group: below primary) | | | | | | |
| Primary school | 0.047** | 0.048 | 0.047** | 0.037** | 0.018 | 0.045** |
| Middle school | 0.144*** | 0.108*** | 0.113*** | 0.134*** | 0.140*** | 0.156*** |
| Secondary school | 0.360*** | 0.303*** | 0.317*** | 0.352*** | 0.381*** | 0.415*** |
| Tertiary graduate | 0.700*** | 0.581*** | 0.636*** | 0.722*** | 0.783*** | 0.835*** |
| Age | 0.040*** | 0.060*** | 0.045*** | 0.038*** | 0.030*** | 0.023*** |
| Age squared | -0.034*** | -0.062*** | -0.042*** | -0.029*** | -0.019*** | -0.009* |
| Scheduled castes | -0.091*** | -0.070*** | -0.045*** | -0.053*** | -0.060*** | -0.082*** |
| Scheduled castes | -0.048* | -0.069 | -0.083*** | -0.056 | -0.080*** | -0.059** |
| Muslim | -0.042*** | -0.065** | -0.043** | -0.058*** | -0.047*** | -0.034** |
| Married | 0.133*** | 0.165*** | 0.173*** | 0.137*** | 0.104*** | 0.087*** |
| Casual worker | -0.314*** | -0.352*** | -0.345*** | -0.334*** | -0.331*** | -0.298*** |
| Casual worker * Primary educated | 0.012 | 0.049 | 0.023 | 0.029 | 0.039 | -0.000 |
| Casual worker * Middle educated | -0.066** | -0.140** | -0.006 | 0.008 | 0.012 | 0.046 |
| Casual worker * Secondary educated | -0.164*** | -0.091 | -0.133*** | -0.246*** | -0.221*** | -0.188*** |
| Casual worker * Tertiary educated | -0.796*** | -1.241*** | -0.658*** | -0.748*** | -0.738*** | -0.442*** |
| Employed in public sector | 0.287*** | 0.518*** | 0.420*** | 0.262*** | 0.167*** | 0.116*** |
| Constant | 3.687*** | 2.692*** | 3.284*** | 3.732*** | 4.246*** | 4.633*** |
| Control for industry (23 industry dummies) | Yes | Yes | Yes | Yes | Yes | Yes |
| Control for states | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 26,135 | 26,135 | 26,135 | 26,135 | 26,135 | 26,135 |
| R-squared | 0.390 | | | | | |

Notes: Because of some missing information on wages, the number of observations in the regression is less than the number of observations reported in Table 2.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

Table 9. OLS and quantile regression, 2004–05

| Regression method | (1) OLS | (2) Q 10 QR | (3) Q 25 QR | (4) Q 50 QR | (5) Q 75 QR | (6) Q 90 QR |
|---|------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Education level (excluded group: below primary) | | | | | | |
| Primary school | 0.055*** | 0.069** | 0.054** | 0.034** | 0.056*** | 0.129*** |
| Middle school | 0.115*** | 0.132*** | 0.136*** | 0.097*** | 0.120*** | 0.138*** |
| Secondary school | 0.376*** | 0.290*** | 0.313*** | 0.335*** | 0.427*** | 0.518*** |
| Tertiary graduate | 0.834*** | 0.693*** | 0.724*** | 0.757*** | 0.910*** | 1.013*** |
| Age | 0.029*** | 0.036*** | 0.018*** | 0.022*** | 0.021*** | 0.026*** |
| Age squared | -0.020*** | -0.032*** | -0.008* | -0.013*** | -0.008*** | -0.012** |
| Scheduled castes | -0.149*** | -0.173*** | -0.129*** | -0.144*** | -0.134*** | -0.133*** |
| Scheduled castes | -0.094*** | -0.069** | -0.097*** | -0.113*** | -0.115*** | -0.087*** |
| Muslim | -0.089*** | -0.091*** | -0.078*** | -0.088*** | -0.073*** | -0.105*** |
| Married | 0.143*** | 0.234*** | 0.161*** | 0.116*** | 0.092*** | 0.089*** |
| Casual worker | -0.396*** | -0.473*** | -0.385*** | -0.370*** | -0.370*** | -0.359*** |
| Casual worker * Primary educated | 0.039 | 0.064 | 0.034 | 0.025 | 0.040*** | -0.059 |
| Casual worker * Middle educated | 0.019 | 0.066 | 0.038 | 0.000 | 0.010 | -0.016 |
| Casual worker * Secondary educated | -0.187*** | -0.052 | -0.176*** | -0.192*** | -0.221*** | -0.315*** |
| Casual worker * Tertiary educated | -0.648*** | -0.716*** | -0.443*** | -0.547*** | -0.788*** | -0.848*** |
| Employed in public sector | 0.510*** | 0.706*** | 0.680*** | 0.598*** | 0.441*** | 0.288*** |
| Constant | 4.069*** | 3.192*** | 3.879*** | 4.212*** | 4.554*** | 4.803*** |
| Control for industry (23 industry dummies) | Yes | Yes | Yes | Yes | Yes | Yes |
| Control for states | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 24,504 | 24,504 | 24,504 | 24,504 | 24,504 | 24,504 |
| R-squared | 0.615 | | | | | |

Notes: Because of some missing information on wages, the number of observations in the regression is less than the number of observations reported in Table 2.

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.