Understanding the causes of widening wage gaps in urban China 1988-2002: evidence from quantile analysis

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Abstract: *This paper examines the change in wage gaps in urban China by estimating quantile regressions on CHIPs data. It applies the Machado and Mata (2005) decomposition, finding the initial sharp rise in inequality from 1988 to 1995 was wholly due to changes in the wage structure. Alongside a less equal wage structure, educational expansion and industrial restructuring played some role in the rise of inequality in 1995-1999. The decompositions do less well in explaining the fall in inequality from 1999 to 2002, although the changes the wage structure and composition of the workforce did play some minor role in that.*

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1. Introduction

Since the start of reform in 1978, there has been concern that China's spectacular economic growth has been partly at the expense of widening inequality. The conventional view is that there is a trade-off between efficiency and equity, with pre-reform China emphasising an egalitarian distribution of earnings the expense of incentives and rewards for private initiative. However, there is a risk that widening inequality may destabilise reform – fostering discontent from the "losers" and thereby engendering social and political instability. In this paper, we focus on one aspect of inequality – wage differentials among urban residents. For example, the ratios of the average wage of the highest paid industry to that of the lowest paid one had increased from 1.76 of 1990 to 4.88 of 2005 (SCDR, 2007; Gu & Feng, 2008). Increasing wage differentials in the urban sector have contributed to a national rise in inequality, although it is only part of the picture (urban unemployment, rural inequality, the rural-urban gap and rural-urban migration also affect national inequality).

Due to data availability, this paper focuses on the period 1988 to 2002. There were several major policy changes during this period that are likely to have changed the wage structure in urban China. Towards the beginning of the period, increased managerial autonomy in state-owned enterprises (SOEs) led to a move away from institutionally determined wages and increased use of bonuses based on enterprise profitability. Following Deng Xiao-ping's "southern tour" in 1992, there was a dramatic increase in the openness of the Chinese economy attracting foreign owned or joint venture firms, as well as exposing domestic firms to international competition as they entered export markets. Controls on rural-urban migration were also relaxed at the same time and the number of rural urban migrants soared from 15 million in 1990 to 98 million in 2003 (News Office of the State Council, 2004). Although migrants were still segmented into specific occupations, there is likely to have been some increase in competition with urban residents for certain kinds of work (for example, low skilled retail or service occupations) (Appleton, *et al*. 2004). Falling profitability in the state owned sector led to radical urban reform in 1995, with a mass retrenchment programme[1]. While this increased urban unemployment, it did not prevent large rises in real wages for workers who retained their jobs (Appleton, *et al*. 2005). Throughout the period there has been a rise in the importance of privately enterprise, whether through new entry of privately owned firms or through changes in the ownership of state owned enterprises (for example, moving to mixed ownership by listing on the stock exchange). The share of the value-added produced by the non-state sectors in GDP increased from 53% in 1992 to 62% in 2001, and in the same period the proportion of urban employment in non-state sectors rose from 39% to 68% even without accounting for jobs being brought about by the rural-urban migrants (NSB, 1993; 2002).

There have been many studies of earnings and inequality in China during this eventful period (see Appleton et al., 2005). However, most analysis of wages has used conventional regression analysis, implicitly focusing on wage differentials at the mean (or, since the dependent variable is typically the log wage, the median). This approach is rather inadequate since inequality depends on the entire distribution of wages – not merely what is happening to the middle of the distribution. Instead, this paper uses quantile analysis in order to map differentials across the entire distribution of wages. This approached, pioneered by Buchinsky (1994) for the US, has been used to track the evolution of wage structures in many different countries. Early applications to urban China have been conducted by Knight and Song (2002) and Bishop, Luo and Wang (2005). However, both these studies are restricted to comparing the urban labour markets in 1988 and 1995, based on the Chinese Household Income Project surveys (CHIPs).

[1] To the end of 2003, the number of the retrenched workers reaches 28.18 million (the News Office of the State Council, 2004). In other words, roughly one-fourth of the SOES workers were retrenched (Appleton, et al. 2002).

This paper goes further by extending the analysis to cover CHIPS data from 1999 and 2002.

Using the results of quantile analysis of wage differentials in 1988, 1995, 1999 and 2002, this paper formally decomposes changes in earnings inequality using the method of Machado and Mata (2005). This technique attributes changes in inequality into two broad sources. The first changes in the wage structure – the coefficients of the quantile regressions. The second is changes in the values of the variables determining earnings - i.e., workers' personal and productive characteristics, and job characteristics. Within these two broad categories, the decomposition also quantifies the contribution of specific determinants of earnings – for example, education – to inequality. We can thus estimate the effect of changing returns to education and a changing stock of education on the gini coefficient for earnings in urban China. Similar estimates are provided for other factors such as experience, gender, Communist party membership, ethnicity, ownership sector, occupation and industrial sector.

The rest of the paper is structured as follows. In section 2, we introduce the data and econometric methods. Sections 3 and 4 give the result of the quantile analysis and the decomposition of wage inequality respectively. Section 5 presents the summary and conclusions.

2. Data and Methods

2.1 Data

We use 1988, 1995, 1999 and 2002 urban household survey data conducted as part of the China Household Income Project. The surveys were designed by a team of international scholars including the authors and researchers at the Institute of Economics of the Chinese Academy of Social Sciences. Sub-samples were drawn from the larger annual national household income survey of the National Bureau of Statistics (NBS). The sub-samples cover 10 out of 31 provinces in 1988, 11 in 1995, 6 in 1999 and 12 in 2002. The questionnaires designed for the Household Income Project are more detailed than those in the official income surveys, particularly with respect to the measurement of income and labor issues. For the cross-sectional analysis, we construct a real wage variable that includes bonuses, price subsidies, which were important in 1988 before being largely withdrawn, regional allowances for working in Tibet or in mountainous areas, income in-kind, and income from secondary jobs.[2] Results from these surveys are in Griffin & Zhao (1993), Riskin et al. (2001), Li & Sato (2006) and Gustafsson, *et al*. (2008) respectively.

These surveys cover only households with urban registration (*hukou*). Consequently, we exclude rural–urban migrant households because they are denied urban *hukou* status. However, estimating wage functions of urban residents separately from those of migrants is appropriate because administrative controls make it extremely difficult for people of rural origin to acquire an urban *hukou* so that any sample selection bias is likely to be negligible. Confining the analysis to the sub-population having the urban *hukou* allows us to examine what causes the enlargement of wage inequality for a specific group of people so that we may draw inferences about corresponding changes in economic well-being. Nonetheless, we are omitting an important dimension of the urban labor market by not being able to include migrants. Moreover,

[2] Our wage variable, although fairly comprehensive, does exclude some non-monetary benefits such as pension accruals, health insurance and housing. The contributions of these variables may vary under differing forms of ownership and over time. Nominal wages were converted into real wages by deflating by regional urban CPIs.

the importance size of this omission has increased over time with the sharp increase in rural–urban migration during the period. Controls over rural–urban migration were loosened significantly in 1988 when the government allowed farmers to conduct business in cities, as Linge and Forbes (1990) discuss. The rise in rural–urban migration is likely to have affected particular groups of urban workers differentially. Specifically, rural–urban migration is likely to have had a moderating impact on the wages of urban residents having similar characteristics as, or working in similar sectors to, migrants. Hence, the effect is greater on urban workers with less education and those working in the service and commercial sectors.[3]

Table 1 reports indicators of inequality in urban wages for our four years of data. The gini coefficient – and all other rose indicators of inequality - sharply in the first interval, from 0.237 in 1988 to 0.345 in 1995. The rise continued in the next interval, although at a much reduced rate, ending with a gini coefficient of 0.375 in 1999. In the most recent interval, inequality has fallen somewhat – the gini coefficient of 0.348 in 2002 is close to that for 1995. The ratios of high and low wage percentile point values give some insight into what this rise in wage inequality has meant. For example, the ratio of the 90th to 10th percentile soared from 2.82 in 1988 to 4.96 in 2002.

When modelling wages, our explanatory variables can be largely divided into worker characteristics and job characteristics, with the additional of a set of dummy variables for provinces. Among the worker characteristics we identify as productive characteristics two conventionally taken to capture human capital – namely years of education and years of (potential) experience, the latter being entered as a quadratic[4]. Other worker characteristics – sex, Communist Party member, non-Han Chinese ethnicity – we label non-productive characteristics as *prima facie* they do seem likely to directly affect productivity. It has been hypothesised that the transition from a command economy to a market-oriented one will see a rise in the remuneration of productive characteristics and a fall in the importance of non-productive ones (Nee, 1989). Among job characteristics, we distinguish the ownership sector of the enterprise the worker is employed in (state owned enterprise, privately owned etc.), the occupation type and the industrial sector (mining, manufacturing etc.). The means of our explanatory variables are given in Table 2, although we delay discussion of the trends apparent in our data until Section 4.

2.2 Method

Let $Q_\theta(w_{it}|X_{it})$ for $\theta \in (0,1)$ denote the θth quantile of the (log) wages w of an individual i in year t for given explanatory variables, X. For each year separately, we model these conditional quantiles by:

$$\mathbf{Q}_\theta\left(w_{\mathbf{it}} \,\vdots\, \mathbf{X}_{\mathbf{it}}\right) = \mathbf{X}'_{\mathbf{it}}\boldsymbol{\beta}_{\mathbf{t}}(\boldsymbol{\theta}) \tag{1}$$

where $\beta(\theta)$ is a vector quantile coefficients and X is a vector of explanatory variables. The coefficients are estimated following Koenker and Bassett's (1978) quantile regression

[3] In the 1999 survey, the more settled migrants were surveyed and so we can compare their characteristics with those of workers with urban *hukou* (see Table 1 of Appleton *et al.,* 2004). Over half the migrants were self-employed and so may not be directly competing for jobs with urban residents (only around 1% of whom were self-employed). Migrants tended to be less educated (averaging three fewer years of education), as well as including more young and male workers. Migrants' distribution across jobs was very different from urban residents, with a large concentration being service or retail workers and relatively few working as highly skilled or industrial workers.

[4] Potential experience is measured as age in years minus (years of schooling plus six).

estimator. In practice, we run a thousand quantile regressions with equally distanced quantile points for each round of the four rounds of cross-sectional data.[5] Afterwards, we plot a curve for the 1000 coefficients on a given explanatory variable against the 1000 quantile points for each year (see Figures 1 to 20). From these curves we can observe the effect of the variable across the range of wage earners and over time.

The quantile regression has a number of advantages over conventional ordinary least squares regressions. Most importantly, it provides a complete representation of the conditional distribution of wages whereas the conventional regression focuses only on the conditional mean[6]. This is particularly crucial for understanding inequality where the standard regression's focus only on the central tendency is very limited. Furthermore, the quantile approach allows one to test whether some determinants of wages have different effects on workers higher up the conditional wage distribution than on those lower down. For example, we can see whether the returns to education vary at different points of the conditional wage distribution. The quantile approach recognises the unobserved heterogeneity of workers and thus allows a richer picture of the determinants of wages to be obtained.

Some care must be taken in interpreting the results of the quantile analysis, because they pertain to *conditional* quantiles, not unconditional ones. Thus a worker at a high wage quantile would be one who has high wages given their values of observed determinants of wages, X, rather than a simply a high wage worker per se. Another way of saying this, is that a worker at high wage quantile will tend to have favourable unobserved determinants of wages, which show the difficulty in interpreting the results. Since unobserved determinants of wages are unobserved, it is not clear exactly what they are. They could include measurement error, for example, or random factors (a worker's good fortune in chancing upon a high paying position). However, there is some interest in these unobservables – for example, unobserved personal characteristics affecting earnings are often labelled "ability" in the theoretical literature (although they may also encompass determination, ambition and factors such as personal appearance). Often we have strong priors about how education will affect the earnings of workers of different ability. Unobserved characteristics of a job may also be interesting – for example, we do not observe firm size or profitability, but rent-sharing theories imply these may have significant effects on earnings. In our exposition, for brevity, when describing the patterns in our findings, we often refer to high quantiles unconditionally as representing high wage workers – as is common in the applied literature – but this is an over-simplification and the more nuanced interpretation focusing on unobservables is often invoked when trying to explain our results.

From our estimates of equation (1) for different years, we can identify the change in the wage structure. This can then be used, following Machado and Mata's (2005) method, to decompose changes in wage inequality into changes attributable to two sources. One is the change in the distribution of explanatory variables, i.e., the change in workers' personal and productive characteristics, and in job characteristics. The other is the change in wage structure in terms of the coefficients on the various explanatory variables. In detail, following Machado and Mata (2005), if $\alpha(.)$ is some summary statistics for wages – such as the gini coefficient – then we can decompose the changes in α as below:

[5] The distance between any two quantile points is 0.001.

[6] Other advantages of the quantile approach are that it is less sensitive to outliers; more robust to departures from normality (Koenker and Bassett, 1978); and has better properties in the presence of heteroscedasticity (Deaton, 1992)

$$
\begin{aligned}
&\alpha\left(f\left(w(1)\right)\right)-\alpha\left(f\left(w(0)\right)\right)\\
&=\underbrace{\left[\alpha\left(f^*\left(w(1);X(0)\right)\right)-\alpha\left(f^*\left(w(0)\right)\right)\right]}_{\text{coefficients}}+ \qquad (2)\\
&\underbrace{\left[\alpha\left(f^*\left(w(1)\right)\right)-\alpha\left(f^*\left(w(1);X(0)\right)\right)\right]}_{\text{covariate}}+ residual.
\end{aligned}
$$

where $f(w(t))$ denotes an estimator of the marginal density of w (the log wage) at t based on the observed sample $\{w_i(t)\}$, $f^*(w(t))$ an estimator of density of w at t based on the generated sample $\{w_i^*(t)\}$, and t=0, 1. The counterfactual densities will be denoted by $f^*(w(1); X(0))$, for the density that would result in t=1 if all covariates had their t=0 distributions, $f^*(w(1); X^i(0))$, for the wage density in t=1 if only X^i (part of the covariates) were distributed as in t=0.

Furthermore, the contribution of an individual covariate x_i to the total wage inequality could be measured by looking at indicators such as

$$\alpha\left(f^*\left(w(1)\right)\right)-\alpha\left(f^*\left(w(1);x_i(0)\right)\right). \qquad (3)$$

Along the line of Machado and Mata, we also propose to counterfactually measure the contribution of an individual coefficient β_i to the change of wage inequality by observing

$$\alpha\left(f^*\left(w(0);\beta_i(1)\right)\right)-\alpha\left(f^*\left(w(0)\right)\right) \qquad (4)$$

where $f^*\left(w(0);\beta_i(1)\right)$ denotes an estimator of density of w with all covariates at period 0 and all coefficients but $\beta_i(1)$ based at period 0, $\beta_i(1)$ denotes the coefficient of x_i is taken from period 1. With Formula (4), we then counterfactually analyze the change of wage inequality and wage gap caused by the specific changes in the pay structure, such as by changes in the returns to education, etc.

In essence, Machado and Mata's counterfactual decomposition is an extension of Oaxaca's (1973) in the environment of quantile regressions.[7] The key exercise of Machado and Mata's approach is to obtain the generated sample $\{w_i^*(t)\}$. To get $\{w_i^*(t)\}$, one first needs to get number n of quantile regression coefficients $\hat{\beta}^t(u_i)$ (where u_i denotes the quantile point), and then generate a random sample of size n with replacement from the rows of $X(t)$ denoted by $\{x_i^*\}_{t=1}^n$, and finally get $\{w_i^*(t)=x_i^*(t)'\hat{\beta}^t(u_i)\}_{t=1}^n$. For details, the reader is referred to Machado and Mata (2005).

[7] As is well known, there is a potential index number problem with such exercises.

3. Results from Quantile Regressions

Figures 1 to 24 present the coefficients from quantile regressions for wages in 1988, 1995, 1999 and 2002.

The enlargement of wage gaps and productive characteristics of workers

In our data, there are two worker characteristics that are *prima facie* productive: education and experience. We discuss the changes in the returns to both characteristics in turn.

Apart from confirming previous findings that the return to education has been steadily rising in urban China (Appleton, et al. 2005; Zhang, et al. 2005), Figure 1 also shows that this rise has been across the entire distribution of wages: the graph for 2002 dominates that for all previous years. However, the increase has been greatest at the higher end of the wage distribution. In general, rising returns to education over time leads to an increase of wage differentials - this has been observed in other transitions, such as those in Eastern Europe (Svejnar, 1999). But in urban China, this is likely to be particularly pronounced, because the rise is most marked at the top end of the distribution. Previous quantile regression analyses of wages in urban China have found that the returns to education appear to be greater at the lower end of the distribution (Knight and Song, 2002; Bishop, Luo and Wang, 2005). For example, Figure 1 shows the return to education at the bottom end of the wage distribution to be around 4% in 1988 but only around 1.5% at the top end. However, over successive surveys, returns to education have increased across the board, but have done so more for higher paid workers. A new finding of this paper is that by 2002, this tendency for returns to education to rise more at the top of the wage distribution has completely eroded the previously observed pattern of greater returns to education for lower paid workers. By 2002, there is little discernible difference in the returns to education across the wage distribution.

Why should returns to education have risen most at the higher end of the wage distribution? It is often argued that the returns to education will be greater at the higher end of the wage distribution because it is assumed that education complements unobserved worker ability. This explanation was used by Buchinsky (1994) to account for the pattern of returns found in his pioneering quantile analysis of wages in the US. However, this pattern is not what we observe in urban China - neither in 2002, where there is no discernible pattern; nor in earlier years, when returns to education were higher for *lower wage* urban worker - the opposite of what Buchinsky observed for the US. How can the seemingly perverse earlier pattern be explained and why has it disappeared during the transition? Buchinsky's explanation of the positive correlation between education returns and conditional wages rested on how returns varied with the unobserved characteristics of *workers*. To explain the contrary pattern in China, Knight and Song (2002) instead focused on the unobserved characteristics of *firms*. Workers at the higher end of the conditional wage distribution are likely to come from firms that pay more, *ceteris paribus*, perhaps because they are more profitable and share some of these rents with their workforce. In urban China, it was common for higher profit firms to supplement basic pay with profit-related bonuses. However, these bonuses were typically distributed quite evenly across their employees and thus not related to worker's productive characteristics such as education. Consequently, in the early reform era of profit-related bonuses, overall earnings might be expected to vary more with education at the lower end of the distribution than at the top. Why might this pattern have disappeared over time? The environment for urban enterprises in China during the period has become more competitive for several reasons: increased openness and consequent need to compete internationally for export markets; greater managerial autonomy within the state owned sector; and the rise of private enterprise. Increased competition has led to falls in the profitability of many Chinese urban enterprises - significant proportion becoming loss-making and having to either retrench or foreclose – leaving fewer bonuses to be distributed. There may also have been a change within firms towards more competitive schemes of remuneration - less rent sharing and, where profit-related pay is used, payment more according to the productivity of the individual employees.

Figure 2 shows that, contrary to the trends with education, the returns to experience fall during China's transition – as was also observed during the East European transitions (Svenjar, 1999). Falls in returns to experience during transition have been explained as a consequence of pre-reform administered wages over-rewarding seniority. However, in urban China, the falls over time have been rather erratic: although returns to experience are lower in 2002 than in 1988, they initially spike upwards in 1995. In all years, the quantile regressions show greater returns to experience at the lower end of the conditional wage distribution. This may be because, as argued with education, there are fewer bonuses at the lower end of the distribution and such bonuses tended to be shared quite equally without regard to seniority. However, it might also be that it was older workers with less favourable unobserved personal characteristics (lower "ability") that tended to benefit more from seniority under administered pay scales. Comparing the results for 2002 and 1988, the fall in returns to experience is much greater for the bottom half of the conditional wage distribution and almost imperceptible at the top[8]. Workers at the top end of the wage scale will therefore have lost the least from falling returns to experience and gained the most from rising returns to education. Both these patterns would tend to lead to widening wage inequality, *ceteris paribus.*

The enlargement of wage gaps and unproductive characteristics of worker

During the period, there has been a rise in the pure gender gap in wages in urban China (Figure 4 refers). This has sometimes been observed in other transitions from communism, but is far from being a universal feature. Newell and Reilly (2001) survey the literature on East and Central European transitions, concluding that the mixed results in different countries means that overall transition is "broadly neutral" in its impact on the pure gender gap. Pham & Reilly () find a fall in the gap in Vietnam in the 1990s. In the Chinese case, it appears that earlier in the reform period, pay scales were more equal between the genders and during the move to the market, there has been more freedom to pay women less[9].

The pattern of gender coefficients across the quantiles follows something of an "L-shape", with much higher gender gaps for lower end of the distribution (although the gaps also start to rise again at the very top end). This is the same as Pham and Reilly find for Vietnam, but contrary to the expectation of a "glass ceiling" effect whereby women at the higher end of the distribution face particular discrimination. Comparing 1988 and 2002, the rise in the pure gender gap appears smaller at the higher end of the distribution. Increasing gender inequalities in pay have

[8] Experience was entered as quadratic in the wage functions and exhibited the conventional inverse U-shaped pattern. Figure 3 shows the turning point of the quadratics remained similar in 1998 and 2002, except for towards the top of the conditional wage distribution, where it rose.

[9] There may also have been selectivity effects, with women forming a smaller share of those in employment after suffering disproportionately from retrenchment in the second half of the 1990s (Appleton et al, 2002). However, one might expect these selectivity effects to *lower* the gender gap, as women with less favourable unobserved characteristics might have been more vulnerable to retrenchment.

arisen more among lower paid workers.

Figure 5 plots the wage premium for Communist Party membership across the conditional wage distribution for the four survey years. Like the pure gender gap, the CP wage premium rises during transition. However, the premium is fairly uniform across the wage distribution in 1988 (albeit somewhat higher at the very top) but in later years increases disproportionately at the lower end of the distribution. It is sometimes argued that CP membership signals high underlying productivity and this - rather than any discrimination in favour of party members - explains the wage premium (ref EJ). However, this is hard to reconcile with the finding of the quantile regression that - after 1988 - CP membership appears to be of most benefit to lower ability workers - those at the lower end of the conditional wage distribution. Bishop, Luo and Wang (2005) suggest that party membership plays a particular role in signalling ability among low earnings workers (who typically lack the educational certificates more conventionally thought to signal ability).

The other non-productive characteristic is ethnicity. Figure 6 plots the coefficients for being non-Han Chinese. Wage gaps appear to be somewhat unfavorable to minorities in 1988 and 1995, then rather favorable in 1999 and 2002. But there are no clear trends with the coefficients for 1988 and 2002 being rather close to each other - and to zero. about the effects of ethnicity on wages during the period. There is also no obvious pattern of variation across the quantiles.

The enlargement of wage gaps and job characteristics of ownership structure

We now turn to the effects on wages of job characteristics, starting with the ownership type of the enterprise in which they work. The default category is state-owned enterprises (SOEs) with dummy variables being used for other types: urban collective; private; foreign owned or joint venture; and "other". The "other" category is sizable only for 2002 and refers to the newly emerging types of ownership whereby firms were listed on the stock market. Typically, this type had mixed ownership - sometimes with the state retaining a dominant share. During the period, there is a marked shift in the share of workers employed in different ownership types, with the emergence of significant numbers of private and foreign companies together with closures and retrenchment in the state owned and urban collective sectors.

Figures 7-10 show the "pure" wage gaps between the various ownership sectors and the default SOE sector. Over time, pay in the urban collective sector has fallen further behind that in SOEs. By contrast, pay in other ownership sectors has risen relative to that in SOEs. As well as shifts in pay differentials by ownership, there have been dramatic changes in how these vary across the distribution. In 1988, the wage premiums for working in an SOE compared to the various types of non-SOEs were greatest at the bottom end of the distribution but sharply diminished as one moves up the distribution. Indeed, at the higher ends of the wage distribution, SOEs paid less *ceteris paribus* than other kinds of enterprise, with the exception of urban collectives. This suggests that lower paid workers may have preferred employment in SOEs, where they would have enjoyed a wage premium, but higher skilled workers may have been better rewarded in the private sector. However, by 2002, the differentials by ownership type were generally much flatter and more uniform across the distribution of wages. A possible explanation for this is that, during the transition, pay in the SOE sector has become less egalitarian and more sensitive to productivity so that there is a close match to the patterns observed in private and foreign owned/joint venture firms.

The enlargement of wage gaps and job characteristics of occupation structure

We have categorised the occupations of workers in our data into private business owners, white collar workers (including professional or technical workers, managers, department heads, clerks), blue collar workers (skilled and unskilled) and others not belong any occupations listed previously. The white collar workers are made as the reference group. Figure 11 shows that the earning differential between private business owners and white collars is almost indiscernible at the median. However, the former earns significantly more than the latter at the upper middle and very top income levels, and this gap is getting bigger over time. Interestingly, by 2002, the earning differential between these two occupations looks like a 25 degree line crossing the horizontal at roughly the middle income level. In other words, comparing with white collars, the earning distribution within private business owners are very unequal with the poor ones earns much less than white collars but the rich ones net much more than the reference group.

There was little difference between the earnings of white collar and blue collar workers in 1988 except for the very lowest paid. However, subsequent years have seen the emergence of a substantial wage gap in favour of white collar workers (Figure 12 refers). The gap is larger at the bottom half of the distribution.

The enlargement of wage gaps and job characteristics of industrial sectors

The industrial sectors of workers in the data are divided into 12 categories as follows: primary sector (including agriculture, forestry, herding, fishing and mining), manufacturing, construction, transportation and communication, commerce (whole sale and retailing), public utilities and real estate (water, gas and electricity supply, real estate, social service), social welfare (health, sports and the like), education and media (education, culture and arts, broadcasting, film and television), sciences and research (scientific research, water control, geological investigation), financial sector, governmental sector, and other not belonging to any sector listed above. The manufacturing sector is set as the reference group. Figures 14-18 plot the coefficients on the dummy variables for the various industrial sectors, showing the pure wage gap between workers employed in them and those in manufacturing. If one were to summarise the overall trends in wage gaps between sectors, perhaps the most marked development has been the erosion of the privileged position of manufacturing workers relative to those in the tertiary sectors (with the exception of commerce). However, it should also be noted that these sectoral differences in pay often also appear to become more varied across the distribution. In 1988, there is a fairly uniform wage premium for manufacturing workers across the whole distribution in 1988 whereas in subsequent years, sectoral wage gaps often vary between high and low earning workers.

One example of how wage gaps increasingly vary over the wage distribution is the primary sector (mining). In 1988, workers in mining enjoyed a small but significant wage premium over manufacturing workers of the order of around 6%. Figure 14 shows that, by 2002, while this premium appears to have increased for the bottom half of the wage distribution, it has been overturned for the top two-fifths. Construction follows an opposite trend: while it appeared to pay somewhat more than manufacturing in 1988, only workers in the top half of the wage distribution earned more in construction than manufacturing in 2002. Those in the bottom half of the distribution earned less in construction in 2002 than comparable workers in manufacturing.

The primary sector (mining) typically enjoys a premium over the reference sector (manufacturing) and for most of the distribution, this has increased since 1988. The exception is the upper tail of the distribution in 2002, where the premium has been eroded. The wage gap between construction and manufacturing has fluctuated over time. In 1988, it was modest and fairly constant over the distribution but in subsequent years, the gap has often been wider but more variable across the distribution. In the most recent year, 2002, the gap was widest towards the end of the distribution whereas for 1999, the reverse was true.

The pay of manufacturing workers has fallen relative to that of comparable workers in most tertiary sectors, specifically: transportation and communication; utilities and real estate; social welfare; education and media; sciences and research, finance; and government. In all of these comparisons, except with transport and communications, manufacturing workers appear to have received a wage premium in 1988 but to be the lower paid in 2002. These shifts in pay appear fairly uniform across the distribution of wages except for utilities and real estate and science research, where the shifts become more marked as we move up the distribution.

The one sector where pay has unambiguously fallen relative to manufacturing is wholesale and retail trade (Figure 17 refers), where the fall is particularly pronounced at the bottom of the wage distribution.

One factor that may underlie some of these changes in pay between sectors is the increase of rural-urban migration during the period. Rural-urban migrants have tended to be concentrated in certain industrial sectors – such as manufacturing and particularly trade - more than others. This increase in competition may have created more of a moderating pressure on the wages of urban residents in those sectors with significant numbers of migrants and so affected differentials with unaffected sectors.

4. Counterfactual analysis - what caused the widening of wage gaps?

After conducting the quantile analysis, we are now able to use the regression results to help explain the widening-up of wage gaps in urban China. As discussed in Section 2, the change of wage inequality can be counterfactually decomposed into that attributable to changes in the covariates of the quantile regressions and that which is attributable to changes in the wage structure (Machado & Mata, 2005). As part of the former, we the impact of changes in worker's personal productive, unproductive and job characteristics contribute to the variation of wage inequality. As part of the latter, we look at the impact on wage inequality of changes in the pay structure, as represented by the shifts in the coefficients of explanatory variables such as sex, education, etc.

Table 4 reports the results of decomposition, using three sub-intervals. Most of the increase in wage inequality took place between 1988 and 1995, when the Gini coefficient rose by 0.107. In aggregate, all of this increase was attributable to changes in the wage structure - to the changes in coefficients discussed previously in Section 3. Changes in the covariates acted to somewhat moderate the rise in inequality, implying a 0.009 fall in the Gini, and the residual of the decomposition was also negative. By contrast, the more modest rise of 0.03 in the Gini from 1995 and 1999 was attributable to both changes in the wage structure (contributing 0.023) and to changes in covariates (0.017) with the residual again being negative. The fall in the Gini coefficient from 1999 to 2002 is not well explained by the decomposition with 0.02 of the aggregate 0.027 point fall being accounted for by the residual. However, both changes in covariates and changes in coefficients played some minor role - accounting for 0.005 and 0.002 points of the fall. To understand these results more properly, we consider the contribution of specific factors to the decomposition, beginning with the productive characteristics of workers.

The change of wage gaps and productive characteristics of workers

Table 3 shows that the average years of schooling of the employed workers and the number of workers in the categories of high school and high-school-above level are increasing over time. This expansion of education had no marked effect on inequality in 1988-95 but contributed strongly to the worsening of inequality thereafter. In the period 1995-99, the expansion accounted for over a third of the rise in the Gini coefficient (0.013 out of a total rise of 0.03, Table 3 refers). The finding that educational expansion, for given wage differentials, widens inequality has been observed in similar decompositions including studies about China (Appleton, et al. 2005; Zhang, et al., 2005; among others) and also studies of developed economies such as America and Europe (Card, 2001; Machado & Mata, 2005). Table 4 provides more detail on the implications of the educational expansion in urban China - showing its impact on relative earnings of different percentile points of the distribution. For example, in the period 1995-99, the expansion would have raised the earnings of the 75th percentile relative to those of the 25th percentile by 5%. The Table also sheds some light on why the expansion did not appear to worsen inequality initially - in particular, in 1988-95, it appears to have narrowed the gap between the wages of the 10th percentile and the 90th percentile (and between the 10th percentile and the median).

Changes in wage differentials by education also played a role in widening inequality. The rise in the returns to education was the second largest contributor to the increase in the Gini coefficient from 1988-95. Increasing returns to education also played a role in the worsening of inequality in the interval 1995-1999, although the contribution was only half of what it was in the previous interval. Table 5 illustrates some of the implications of these coefficient changes on the relative earnings of different percentiles of the wage distribution. For example, the rise in returns to education in 1988-95, *ceteris paribus,* increased the earnings of the 90th percentile relative to the 10th by 8%. The corresponding increases for subsequent intervals were also sizable - 15% in 1995-1999 and 6% in 1999-2000. Overall, therefore, both the expansion of education and the rise in the returns to education contributed to the enlargement of wage gaps in urban China.

In contrast, changes related to the other productive worker characteristic - experience - have tended to reduce wage inequality and wage gap over time. As Table 2 shows, the average years of potential work experience of the urban Chinese labour force has increased somewhat over time. This reflects an aging of the workforce, somewhat offset by an increase in time spent in education (average age rises by 3.4 years between 1988 and 2002 but potential experience rises by only 1.9 years). However, what is important for inequality is not so much the mean level of experience but its dispersion. Over time, there has been a reduction in the proportion of employees with relatively little experience but also in those with very high levels of experience (i.e. with over forty years of experience - these workers are likely to be elderly with little education). These changes have an equalising effect on the Gini coefficient reducing it by 0.04 to 0.05 points in each of the three intervals, 1988-995, 1995-1999 and 1999-2002. Table 4 illustrates this, by showing how changes in the distribution of experience have compressed wage differentials for each pair of percentiles considered in each interval.

Along with the evolution of experience structure, the change of pay structure by experience groups also reduces wage inequality except for the period of 1988-1995. It will be recalled that returns to experience have tended to fall in urban China during the period, although initially they spiked upwards in the interval 1988-95. The general reduction in the importance of seniority has had an equalising effect, which was particular strong in the most recent interval - contributing 0.01 points (over one third of the total) to the fall in the Gini from 1999-2002.

The change of wage gaps and unproductive characteristics of worker

Now we look at other personal factors such as sex, Communist Party (CP) membership and minority status. The changes of sex structure and ratio of workers with CP membership have both increased wage inequality. As Table 2 shows, there has been a fall in women's share of urban employment - mainly due to them having been more at risk of retrenchment in the second half of the 1990s (Appleton *et al*. 2002). There has also been an expansion of CP membership in the country - perhaps not coincidentally taking place at the same time as the wage premium for party membership has risen (Appleton *et al*. 2009). The net effect of an increasingly male workforce is to raise the gini coefficient of wages by 0.001 in 1988-1995, 0.003 in 1995-1999 and 0.002 in 1999-2002; the corresponding figures for CP membership are 0.001 in the first period and 0.003 in both the second and third periods.

The increases in the gender wage gap has also worsened wage inequality, raising the Gini coefficient by 0.003 in 1988-1995, 0.002 in 1995-1999 and 0.001 in 1999-2002. The change in the CP premium only worsens inequality in the middle interval, 1995-1999, although the effect on the gini in that period is non-trivial - increasing it by 0.005 (one sixth of the total rise). There is no effect in the interval 1988-95 since, although the premium increases at the median, Figure 5 reveals it rises most for lower paid workers and falls for the higher paid. In the last period, 1999-2002, the premium falls slightly and this contributes somewhat to the fall in wage inequality in this interval.

Although the proportion of minority workers slightly increases during the period (Table 3), neither the fact of more minority workers nor the change of pay structure by minority status produce any discernible impact on wage inequality or wage gap (Tables 4, 5, 6).

The change of wage gaps and job characteristics of ownership structure

Table 3 documents large changes in employment by ownership, with the contraction of urban collectives and SOEs, and the emergence of private, foreign and "other" (i.e. mixed) forms of ownership. However, Table 3 reveals the impact of these changes on inequality to be rather modest. The largest effect is in the period 1995-99 - the time of retrenchment in the state sector - when the shifts in ownership raise the gini coefficient by 0.003. In the earlier interval, 1988-95, the corresponding change in the gini is 0.001 and in 1999-2002, it is a fall of 0.001.

By contrast, the change of ownership pay structure contributed substantially to the enlargement of wage inequality and wage gaps, with the net effect on Gini is as large as 0.012 in the period of 1988-1995, dropping slightly to 0.010 in the period 1995-1999 but afterwards sharply soaring to 0.045 in 1999-2002 (Table 4). Looking at direct measures of wage differentials (Table 6) also reveals sharp upsurges, particularly in the ratio of the earnings of the 90th percentile to those of the 10th percentile. A key factor here is likely to be the decline in earnings of urban collectives, which tend to employ lower paid workers, and the rise in the premium paid to workers in foreign owned or joint venture companies, who tend to be the highest paid.

The change of wage gaps and job characteristics of occupation structure

The change of occupational structure of the employed workers results in the rise of wage inequality over time (Tables 3 & 4). The shares of private business owners, white collars and other un-classified occupations in employment are all rising over time but the size of blue collars is shrinking in this period (Table 2). The white collars and in particular the private business owners normally earn much more than the blue collars, and the earning gap is expanding over time (Table 1, Figures 11-12). Thus, it should be predicted that this occupational structural evolution results in enlarged wage inequality.

By contrast, the evolution of occupational pay structure gives rise to the fall of wage inequality in the periods of 1995-1999 and 1999-2002, and the reduction of wage gap in the periods of 1988-1995 and 1999-2002 (Tables 3 & 5). In Table 5, the ratios of the 90^{th} percentile wage to the 10^{th} percentile wage were falling in the periods of 1988-1995 and 1999-2002.

The change of wage gaps and job characteristics of industrial sectors

The change in the industrial structure of urban China contributes to the rise of inequality in each interval. The effects are modest in 1988-95 and 1999-2000, implying a 0.004 rise in the gini coefficient in both intervals. However, the contribution is very large in the period of retrenchment, 1995-99, when employment shifts between sectors raise the gini coefficient by 0.21, accounting for a full two thirds of its overall rise. In this period, manufacturing's share of employment falls substantially – as does wholesale and retail trade. Major growth areas are in construction, transport and communications, public utilities and real estate (Table 3). Earnings in these growing sectors tend to vary more across the quantiles than occurs in manufacturing (Figures 15, 16 and 18), which helps explain the consequent rise in inequality.

Changes in industrial pay differentials also affect wage inequality. Again, the contribution is most marked in the period of retrenchment, 1995-99, when they imply a rise in the gini coefficient of 0.017 – more than half of the overall rise observed. But this contribution is exactly reversed in the subsequent period and again explains more than half of the overall change in the gini coefficient. The contribution in the earlier period, 1988-95, is more modest (implying a 0.009 rise in the gini). What appears to be at work is a fall in the pay of manufacturing workers in 1995-99 relative to those working in most other sectors which to some extent is offset by increases in 1999-2002. Since manufacturing workers tend to be lower paid than many in services, the gini coefficient tends to vary inversely with their relative pay.

5. Conclusions

This paper uses quantile analysis to make two broad contributions to the literature on the determinants of earnings and inequality in urban China. First, it tracks the evolution of the wage differentials across the entire distribution of wages rather than merely focusing at the mean or median. Second, it identifies how these changes in the wage structure – and also the profile of employment – have led to rising inequality.

In terms of the first contribution, it is notable that the changes in the returns to productive worker characteristics already documented in the literature appear to adversely affect the relative position of those at the lower end of the wage distribution. Thus although returns to education have risen over time, they have risen least for the lower paid. Conversely, the fall in the returns to experience during the period has been most pronounced at the bottom of the distribution and barely perceptible at the top. The rise in the gender wage gap and in the Communist Party member premium are also most marked at the bottom of the wage distribution.

Some of the changes in wage differentials by job characteristics also appear to worsen the relative position of those lower in the wage distribution. In particular, the fall in the wage premium for working in a State Owned Enterprise is largest for the lower paid. The other marked changes – the fall in the relative pay of manufacturing workers and blue collar workers – appear more uniform across the distribution. However, even then, there is evidence that the wage structure for private business employers, construction workers and those in retail trade has become more unequal – disadvantaging those at the lower end of the wage distribution.

As for the second contribution, it is important to recognise that the causes of wage inequality in China have varied over time. We find that it is the changes in the wage structure alone that explain the initial large rise in inequality in 1988-95. By contrast, they account for two thirds of the further smaller increase in inequality in 1995-99, with changes in worker and job characteristics accounting for the remaining third. In our final interval, 1999-2002, wage inequality actually fell but our decomposition analysis is rather unsuccessful in accounting for this fall – attributing it mainly to a residual.

A number of aspects of the changes in the wage structure were important for explaining the initial rise in inequality in 1988-95: the changes in returns to education and experience, and the changes in wage differentials by ownership and industrial sector. These factors continued to play a role in the continuing widening of wage gaps in 1995-99, although the changing returns to productive worker characteristics somewhat lessened in importance. Additionally, during this period of retrenchment, changes in the industrial structure together with the expansion of education also contributed substantially to the rise in the gini coefficient. Our analysis implies that the changes in the wage structure in the period 1999-2002 generally help explain the more recent fall in wage inequality, with the notable exception of wage differentials by ownership which have been very disequalising.

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Table 1: Gini Coefficients by wages

	1988	1995	1999	2002
Percentile ratios				
p90/p10	2.823	5.044	4.859	4.957
p90/p50	1.570	1.987	2.015	2.084
p10/p50	0.556	0.394	0.415	0.421
p75/p25	1.646	2.170	2.215	2.291
Gini coefficients	0.23720	0.34449	0.37478	0.34781
General entropy				
GE(-1)	0.23790	0.57580	0.51155	0.28577
GE(0)	0.10786	0.23536	0.27438	0.21241
GE(1)	0.10766	0.22646	0.36853	0.21514
GE(2)	0.14837	0.37869	1.56071	0.29688
Atkinson index				
A(0.5)	0.05124	0.10560	0.13791	0.10053
A(1)	0.10224	0.20971	0.23996	0.19137
A(2)	0.32240	0.53523	0.50571	0.36368

Sources: calculated from the CHIP 1988, 1995, 1999 and 2002 urban household survey.

Figure 1. Return to School Years

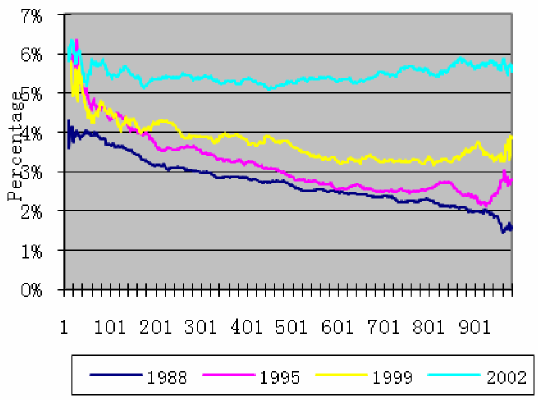

Figure 2. Return to Experience

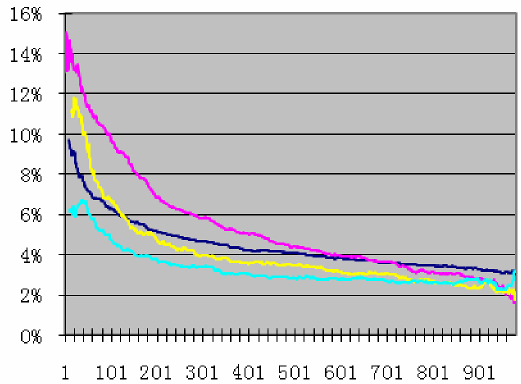

Figure 3. Peak point of experience return

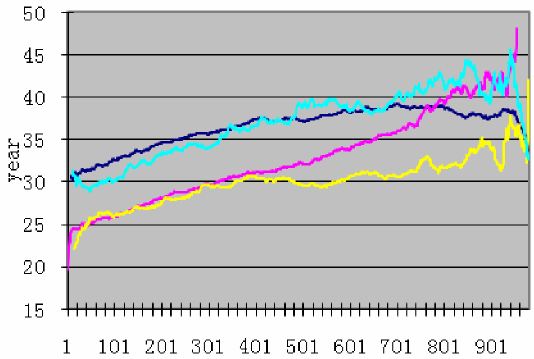

Figure 4. Wage gap of male vs female

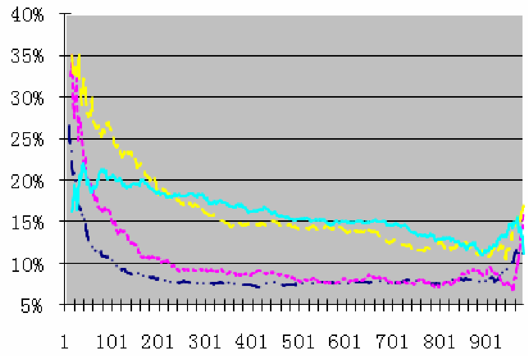

Figure 5. Wage Premium to Communist Party Member

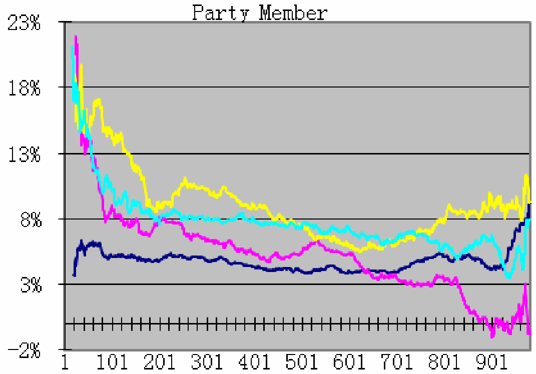

Figure 6. Wage Premium to minority

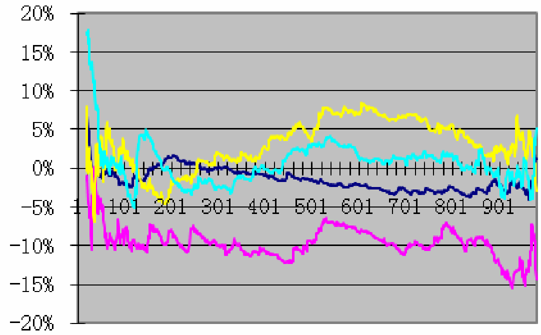

Figure 7. Wage gap between urban collectives with SOEs

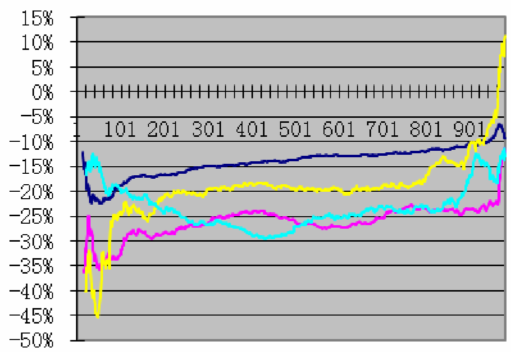

Figure 8. Wage gap between private Firms vs SOEs

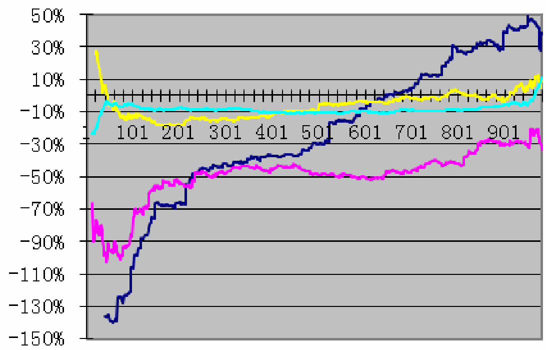

Figure 9. Wage gap between FDI or joint-venture vs SOEs

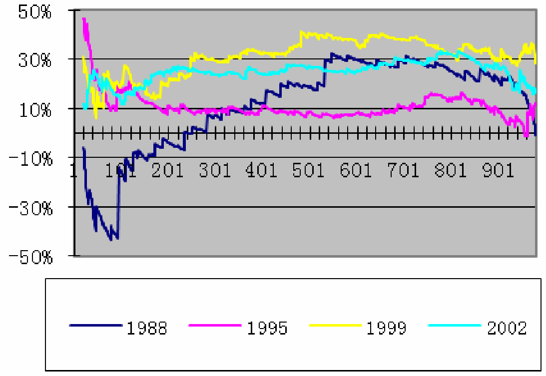

Figure 10. Wage gap between Other Ownerships vs SOEs

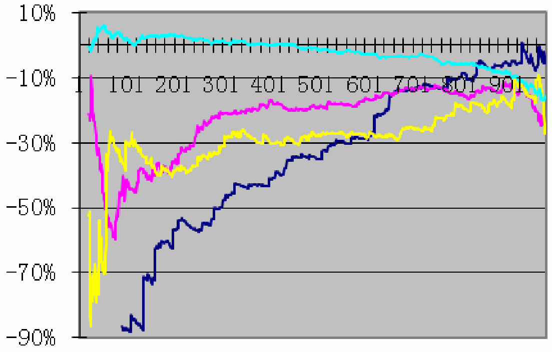

Figure 11. Wage gap between private business owners vs white collar

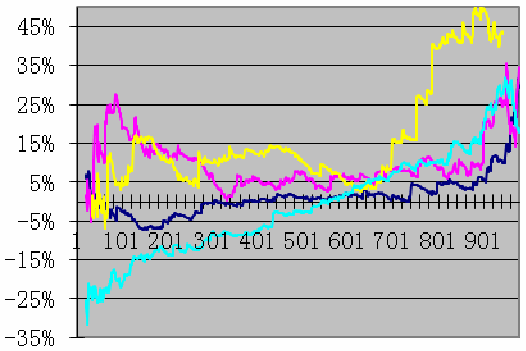

Figure 12. Wage gap between blue collar and white collar

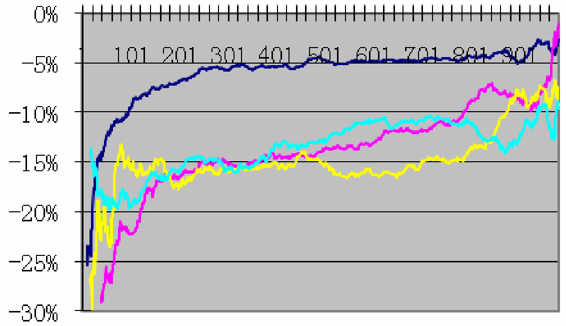

Figure 13. Wage gap between other occupations vs white collar

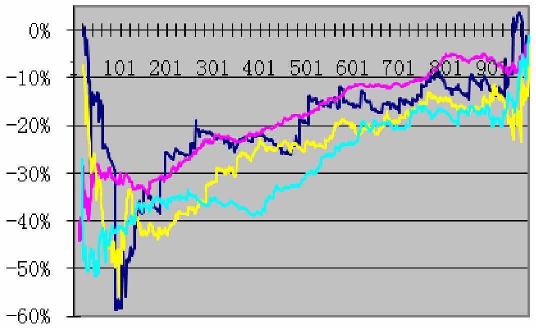

Figure 14. Wage gap between primary sector vs manufacturing sector

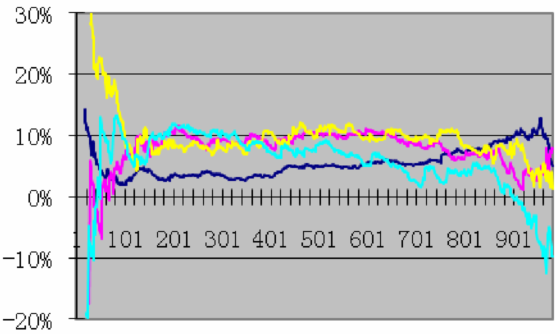

Figure 15. Wage gap between construction vs manufactring sector

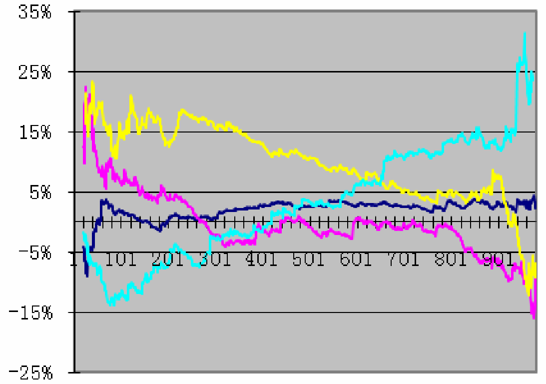

Figure 16. Wage gap between transportation & communication sector vs manufacturing

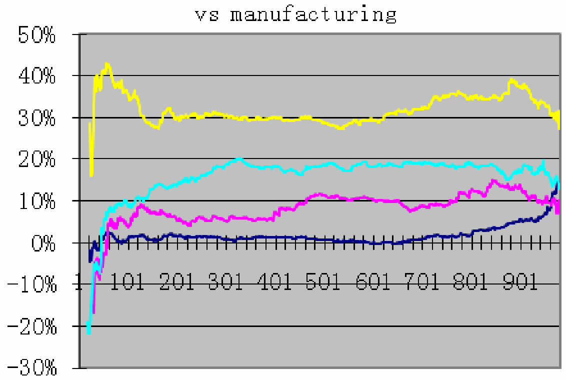

Figure 17. Wage gap between wholesale & retail vs manufacturing

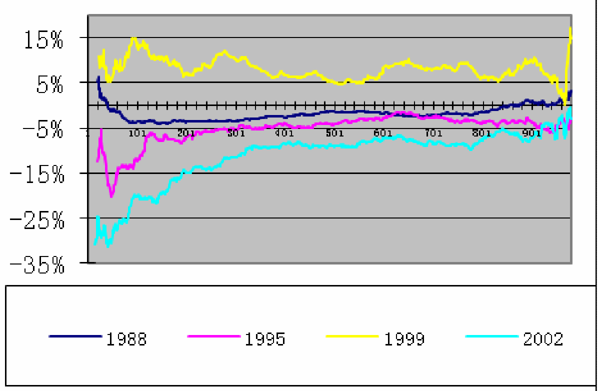

Figure 18. Wage gap between public utilitites & real estate sector vs manufacturing

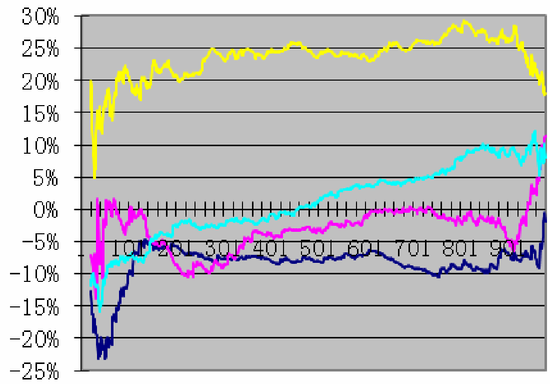

Figure 19. Wage gap between social welfare vs manufacturing

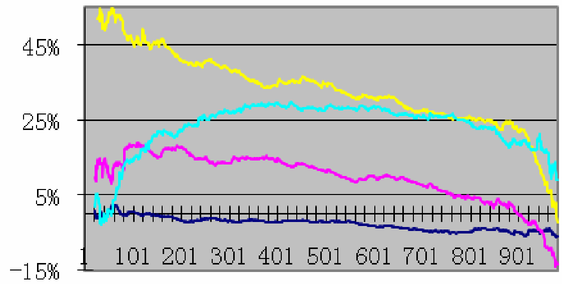

Figure 20. Wage gap between education & media vs manufacturing

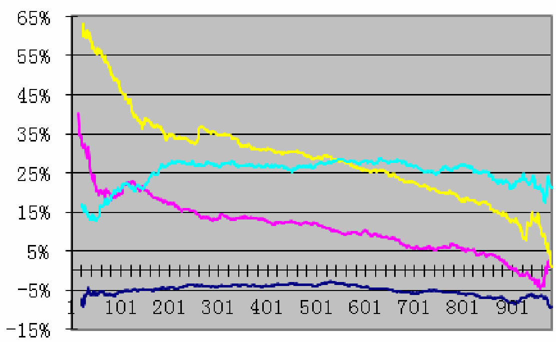

Figure 21. Wage gap between science & research vs manufacturing

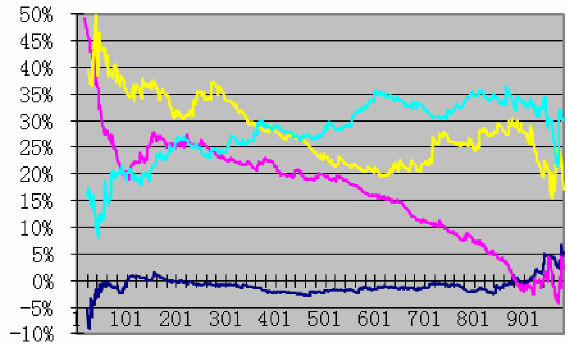

Figure 22. Wage gap between financial sector vs manufacturing

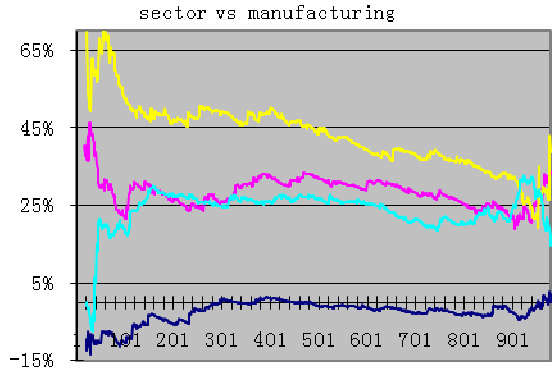

Figure 23. Wage gap between government sector vs manufacturing

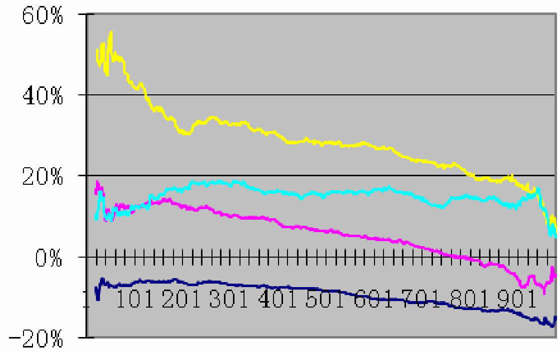

Figure 24. Wage gap between other sectors vs manufacturing

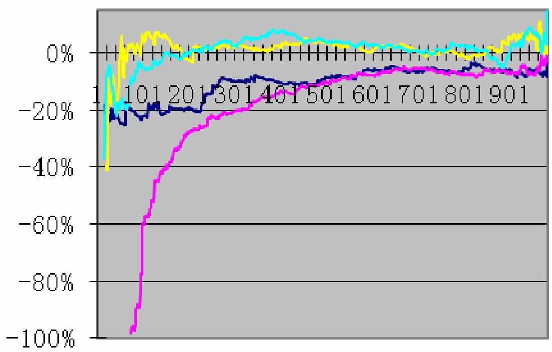

Table 2: personal, productive, unproductive and job characteristics of the workers in data

	1988	1995	1999	2002
Male	52.23%	52.58%	54.16%	55.55%
CP members	23.47%	24.51%	26.89%	28.81%
Minority	3.77%	4.30%	4.17%	4.10%
Education in years	10.04	10.73	11.24	11.46
Age in years	37.10	38.56	39.45	40.45
Experience in years	21.06	21.83	22.21	22.99
Education by levels				
University & above	6.03%	7.86%	9.19%	10.30%
Polytech	6.64%	15.38%	20.00%	22.75%
Technical school	11.01%	16.52%	13.47%	12.56%
High School	24.77%	24.34%	26.11%	28.03%
Secondary school	38.61%	30.36%	28.77%	23.50%
Primary	10.36%	5.11%	2.26%	2.65%
Below primary	2.58%	0.43%	0.21%	0.21%
Experience by levels				
<=10	20.20%	16.47%	14.60%	13.21%
11-20	28.24%	26.96%	26.84%	25.99%
21-30	30.63%	36.26%	36.20%	35.00%
31-40	16.78%	17.18%	20.38%	23.17%
41-50	4.02%	3.05%	1.88%	2.59%
51-60	0.13%	0.08%	0.10%	0.03%
Ownership structure				
SOEs	77.67%	79.04%	77.46%	33.86%
Urban collective	20.28%	15.06%	13.20%	6.86%
Private ownership	0.77%	1.65%	4.59%	20.72%
Foreign owned or Joint venture	0.36%	1.27%	1.99%	2.17%
Other ownership	0.92%	2.98%	2.77%	36.39%
Occupation				
Private business owners	1.21%	1.47%	1.42%	4.63%
White collar	45.42%	52.83%	50.18%	51.63%
Blue collar	52.76%	37.44%	45.49%	40.47%
Other occupations	0.60%	8.26%	2.91%	3.27%
Industrial sectors				
Primary	4.13%	2.65%	3.53%	2.78%
Manufacturing	42.72%	39.86%	31.73%	24.96%
Construction	3.41%	2.87%	4.35%	3.23%
Transportation and comm.	6.74%	4.86%	9.25%	7.77%
Wholesale & retail	14.41%	14.23%	10.79%	12.20%
Public utilities and real estate	2.45%	3.81%	10.64%	14.65%
Social welfare	4.55%	4.39%	4.43%	5.07%
Education and media	7.21%	7.11%	7.28%	8.96%
Sciences and research	2.89%	2.27%	2.18%	2.56%
Financial sector	1.53%	1.92%	2.07%	2.67%
Government	8.42%	11.32%	8.82%	11.91%
Other industries	1.52%	4.71%	4.94%	3.25%

Sources: calculated from the CHIP 1988, 1995, 1999 and 2002 urban household survey.

Table 3: Decomposition of the changes in the wage distribution

	1988-1995	1995-1999	1999-2002
Change of Gini	0.107	0.030	-0.027
Aggregate contributions to the change of Gini coefficient			
Covariates	**-0.009** (-0.017, 0.017)	**0.017** (-0.078, 0.122)	**-0.005** (-0.018, 0.003)
Coefficients	**0.126** (0.095, 0.142)	**0.023** (-0.044, 0.084)	**-0.002** (-0.024, 0.019)
Residual	**-0.010** (-0.027, 0.019)	**-0.010** (-0.100, 0.070)	**-0.020** (-0.042, 0.015)
Contribution to the net change of Gini coefficient by covariates			
Sex	**0.001** (-0.003, 0.006)	**0.003** (-0.002, 0.012)	**0.002** (0.000, 0.004)
CP membership	**0.001** (0.000, 0.002)	**0.003** (-0.003, 0.011)	**0.003** (0.001, 0.004)
Minority	**0.000** (-0.003, 0.001)	**-0.001** (-0.007, 0.001)	**0.000** (-0.001, 0.001)
Education	**-0.001** (-0.012, 0.011)	**0.013** (-0.014, 0.053)	**0.003** (-0.001, 0.008)
Experience	**-0.004** (-0.012, 0.004)	**-0.005** (-0.014, 0.000)	**-0.005** (-0.012, -0.002)
Occupation	**0.001** (-0.007, 0.006)	**0.001** (-0.009, 0.006)	**0.007** (0.003, 0.010)
Ownership	**0.001** (-0.004, 0.007)	**0.003** (-0.011, 0.013)	**-0.001** (-0.005, 0.003)
Industrial sector	**0.004** (-0.006, 0.012)	**0.021** (-0.054, 0.106)	**0.004** (-0.010, 0.017)
Contribution to the net change of Gini coefficient by covariate's coefficient			
Sex	**0.003** (0.002, 0.004)	**0.002** (-0.002, 0.005)	**0.001** (-0.012, 0.006)
CP membership	**0.000** (-0.001, 0.001)	**0.005** (0.004, 0.007)	**-0.001** (-0.009, 0.002)
Minority	**0.000** (0.000, 0.001)	**0.000** (-0.001, 0.000)	**0.000** (-0.001, 0.000)
Education	**0.010** (0.008, 0.013)	**0.005** (-0.003, 0.023)	**-0.001** (-0.053, 0.019)
Experience	**0.008** (0.006, 0.012)	**-0.002** (-0.010, 0.003)	**-0.010** (-0.019, -0.004)
Occupation	**0.000** (-0.001, 0.002)	**-0.008** (-0.015, -0.003)	**-0.003** (-0.015, 0.001)
Ownership	**0.012** (0.009, 0.016)	**0.010** (0.006, 0.017)	**0.045** (0.028, 0.065)
Industrial sector	**0.009** (0.005, 0.014)	**0.017** (0.010, 0.026)	**-0.017** (-0.112, 0.036)
Constant	**0.083** (0.071, 0.102)	**0.109** (0.069, 0.212)	**-0.044** (-0.136, 0.007)

Note: (1) The net change of Gini coefficient is the mean of 10 times replication of the simulation with the 1000 random sample drawn from the variable data set and coefficients from quantile regressions data sets with replacement. During each simulation, once the random samples are drawn, they will be used throughout the simulation. (2) The maximum and minimum values of the 10 times replication is shown in the bracket.

Table 4: Change of the ratio of different percentile point earnings caused by the change of covariates

	p90/p10	p90/p50	p10/p50	p75/p25
1988-1995				
Sex	**0.01** (-0.14, 0.06)	**0.01** (-0.02, 0.04)	**0.00** (-0.01, 0.01)	**0.02** (-0.04, 0.07)
CP membership	**0.05** (-0.07, 0.20)	**0.00** (-0.03, 0.03)	**0.00** (-0.02, 0.00)	**0.02** (-0.01, 0.05)
Minority	**0.00** (-0.03, 0.03)	**0.00** (-0.02, 0.02)	**0.00** (0.00, 0.00)	**0.00** (-0.01, 0.02)
Education	**-0.06** (-0.25, 0.22)	**0.02** (-0.05, 0.11)	**0.01** (-0.02, 0.03)	**0.00** (-0.08, 0.09)
Experience	**-0.24** (-0.52, 0.02)	**-0.03** (-0.07, 0.05)	**0.01** (-0.01, 0.05)	**-0.04** (-0.14, 0.03)
Occupation	**0.14** (0.07, 0.23)	**-0.01** (-0.04, 0.04)	**-0.01** (-0.03, 0.00)	**0.05** (-0.03, 0.11)
Ownership	**0.07** (-0.21, 0.22)	**0.00** (-0.04, 0.06)	**0.00** (-0.02, 0.01)	**0.02** (-0.10, 0.09)
Industrial sector	**0.08** (-0.23, 0.31)	**0.01** (-0.07, 0.08)	**-0.01** (-0.02, 0.01)	**0.02** (-0.02, 0.06)
1995-1999				
Sex	**0.02** (-0.16, 0.20)	**0.02** (-0.04, 0.12)	**0.00** (-0.01, 0.02)	**0.02** (-0.04, 0.06)
CP membership	**0.09** (-0.06, 0.32)	**0.02** (-0.02, 0.06)	**0.00** (-0.02, 0.02)	**0.03** (-0.01, 0.06)
Minority	**0.01** (-0.01, 0.12)	**0.00** (-0.01, 0.02)	**0.00** (-0.01, 0.00)	**0.00** (-0.01, 0.02)
Education	**0.05** (-0.28, 0.51)	**0.04** (-0.04, 0.15)	**0.00** (-0.03, 0.03)	**0.05** (-0.02, 0.15)
Experience	**-0.11** (-0.37, 0.22)	**-0.02** (-0.11, 0.03)	**0.01** (-0.01, 0.03)	**-0.02** (-0.07, 0.02)
Occupation	**0.11** (-0.09, 0.28)	**0.03** (-0.02, 0.09)	**0.00** (-0.02, 0.02)	**0.06** (0.02, 0.10)
Ownership	**0.14** (0.00, 0.30)	**0.02** (-0.02, 0.06)	**-0.01** (-0.02, 0.01)	**0.07** (0.02, 0.11)
Industrial sector	**0.13** (-0.12, 0.51)	**0.00** (-0.14, 0.09)	**-0.01** (-0.03, 0.01)	**0.07** (0.02, 0.12)
1999-2002				
Sex	**0.07** (-0.18, 0.31)	**0.02** (-0.03, 0.10)	**0.00** (-0.03, 0.02)	**0.01** (-0.07, 0.06)
CP membership	**0.09** (-0.09, 0.28)	**0.03** (-0.02, 0.07)	**0.00** (-0.01, 0.01)	**0.02** (-0.01, 0.06)
Minority	**0.00** (-0.02, 0.04)	**0.00** (-0.01, 0.00)	**0.00** (0.00, 0.00)	**0.00** (-0.01, 0.01)
Education	**0.18** (-0.10, 0.50)	**0.04** (-0.04, 0.18)	**-0.01** (-0.02, 0.01)	**0.07** (-0.01, 0.19)
Experience	**-0.09** (-0.34, 0.17)	**-0.02** (-0.07, 0.03)	**0.00** (-0.02, 0.03)	**-0.05** (-0.11, 0.00)
Occupation	**0.24** (0.06, 0.55)	**0.03** (-0.04, 0.09)	**-0.02** (-0.03, 0.00)	**0.05** (-0.03, 0.10)
Ownership	**0.01** (-0.14, 0.15)	**-0.01** (-0.05, 0.02)	**0.00** (-0.02, 0.01)	**0.02** (-0.03, 0.06)
Industrial sector	**0.28** (-0.09, 0.45)	**0.02** (-0.06, 0.08)	**-0.02** (-0.03, 0.00)	**0.09** (0.02, 0.13)

Note: (1) The net change of the ratios is the mean of 10 times replication of the simulation with the 1000 random sample drawn from the variable data set and coefficients from quantile regressions data sets with replacement. (2) The maximum and minimum values of the 10 times replication is shown in the bracket.

Table 5: Change of the ratio of different percentile point earnings caused by the change of covariate coefficients

	p90/p10	p90/p50	p10/p50	p75/p25
		1988-1995		
Sex	**0.23** (0.16, 0.32)	**0.04** (0.00, 0.08)	**-0.01** (-0.02, 0.00)	**0.04** (0.02, 0.08)
CP membership	**0.06** (0.00, 0.14)	**0.01** (0.00, 0.03)	**0.00** (-0.01, 0.00)	**0.01** (0.00, 0.02)
Minority	**-0.02** (-0.08, 0.01)	**-0.01** (-0.04, 0.00)	**0.00** (0.00, 0.00)	**-0.01** (-0.02, 0.00)
Education	**0.08** (-0.03, 0.18)	**0.04** (0.00, 0.09)	**0.00** (0.00, 0.01)	**0.03** (0.00, 0.07)
Experience	**-0.23** (-0.40, 0.02)	**0.00** (-0.04, 0.06)	**0.02** (0.01, 0.03)	**-0.03** (-0.09, 0.03)
Occupation	**-0.12** (-0.19, 0.00)	**-0.02** (-0.06, 0.01)	**0.01** (0.00, 0.01)	**-0.03** (-0.04, -0.01)
Ownership	**0.61** (0.32, 1.17)	**0.13** (0.08, 0.21)	**-0.02** (-0.06, 0.00)	**0.09** (0.04, 0.14)
Industrial sector	**0.31** (0.09, 0.63)	**0.06** (-0.03, 0.12)	**-0.01** (-0.03, 0.01)	**0.05** (0.00, 0.13)
Constant	**-0.35** (-0.77, 0.11)	**0.18** (0.03, 0.35)	**0.07** (0.03, 0.10)	**0.02** (-0.12, 0.19)
		1995-1999		
Sex	**0.06** (0.00, 0.11)	**0.01** (0.00, 0.04)	**-0.01** (-0.02, 0.00)	**0.02** (0.00, 0.05)
CP membership	**0.02** (-0.01, 0.06)	**0.01** (0.00, 0.02)	**0.00** (-0.01, 0.00)	**0.01** (0.00, 0.02)
Minority	**0.01** (-0.01, 0.05)	**0.00** (-0.01, 0.01)	**0.00** (-0.01, 0.00)	**0.00** (-0.01, 0.01)
Education	**0.15** (0.06, 0.28)	**0.07** (0.03, 0.13)	**0.00** (-0.03, 0.02)	**0.05** (0.00, 0.07)
Experience	**0.08** (-0.08, 0.18)	**0.05** (0.01, 0.07)	**0.00** (-0.02, 0.02)	**0.04** (0.02, 0.07)
Occupation	**0.00** (-0.06, 0.04)	**0.01** (0.00, 0.04)	**0.01** (-0.01, 0.02)	**0.02** (-0.02, 0.04)
Ownership	**0.19** (0.15, 0.27)	**0.07** (0.04, 0.09)	**-0.01** (-0.03, 0.00)	**0.07** (0.05, 0.09)
Industrial sector	**0.16** (0.03, 0.21)	**0.05** (0.02, 0.09)	**-0.01** (-0.02, 0.00)	**0.03** (0.00, 0.06)
Constant	**1.51** (1.10, 2.14)	**0.40** (0.31, 0.49)	**-0.10** (-0.15, -0.05)	**0.44** (0.35, 0.52)
		1999-2002		
Sex	**0.22** (0.04, 0.32)	**0.02** (-0.02, 0.06)	**-0.01** (-0.02, -0.01)	**0.06** (0.01, 0.11)
CP membership	**0.16** (0.07, 0.29)	**0.04** (0.01, 0.10)	**0.00** (-0.01, 0.00)	**0.03** (0.02, 0.05)
Minority	**0.00** (-0.01, 0.03)	**0.00** (-0.01, 0.01)	**0.00** (0.00, 0.00)	**0.00** (-0.02, 0.02)
Education	**0.06** (-0.10, 0.18)	**0.07** (0.02, 0.13)	**0.01** (0.00, 0.02)	**0.05** (0.02, 0.07)
Experience	**-0.28** (-0.74, -0.08)	**-0.01** (-0.07, 0.04)	**0.02** (0.01, 0.05)	**-0.02** (-0.07, 0.02)
Occupation	**-0.20** (-0.40, -0.07)	**-0.01** (-0.06, 0.04)	**0.02** (0.01, 0.02)	**-0.02** (-0.05, 0.01)
Ownership	**0.26** (0.04, 0.40)	**0.06** (0.02, 0.09)	**-0.01** (-0.02, 0.00)	**0.07** (0.04, 0.12)
Industrial sector	**0.39** (0.19, 0.58)	**0.13** (0.08, 0.17)	**-0.01** (-0.02, 0.01)	**0.11** (0.05, 0.21)
Constant	**1.11** (0.03, 2.01)	**0.31** (0.11, 0.50)	**-0.02** (-0.05, 0.04)	**0.17** (-0.06, 0.41)

Note: (1) The net change of the ratios is the mean of 10 times replication of the simulation with the 1000 random sample drawn from the variable data set and coefficients from quantile regressions data sets with replacement. (2) The maximum and minimum values of the 10 times replication is shown in the bracket.