www.elsevier.com/locate/worlddev

World Development Vol. 62, pp. 1–13, 2014
0305-750X/
http://dx.doi.org/10.1016/j.worlddev.2014.04.005

Understanding Urban Wage Inequality in China 1988–2008: Evidence from Quantile Analysis

SIMON APPLETON [a], LINA SONG [a] and QINGJIE XIA [b,*]
[a] *University of Nottingham, Nottingham, UK*
[b] *Peking University, Beijing, China*

Summary. — This paper examines change in wage gaps in urban China from 1988 to 2008 by estimating quantile regressions on CHIPS data. It applies the Machado and Mata (2005) decomposition, finding sharp increases in inequality largely due to changes in the wage structure. During 2002–08, changes in the returns to education and experience have been equalizing. However, changes in other categories of wage differential—by sex, occupation, ownership, industrial sector, and province—widened inequality. The gender gap continued to rise, as did the gap between white collar and blue collar workers, and between manufacturing and other sectors.

Key words — China, labor, wages, quantile regression, inequality

1. INTRODUCTION

Rising inequality is a serious concern for China. Over the last few decades, China has experienced soaring GDP growth but at the same time, widening income inequalities. Conventionally, rising income inequality in transitional economies has been viewed as a necessary trade-off for increased efficiency, with pre-reform China emphasizing an egalitarian distribution of earnings the expense of incentives and rewards for private initiative. Yet widening inequality may destabilize the economy—fostering socio-political discontent from the "losers" and thereby engendering instability.

The rise of wage inequality in urban China has been analyzed by a number of authors. However, most analysis of wages has used conventional regression analysis, implicitly focusing on wage differentials at the mean—see, for example, Ge and Yang (2012) and Meng, Shen and Xue (2012). Conventional regression analysis is limited since inequality depends on the entire distribution of wages—not merely what is happening to the middle of the distribution—and the parameters of a regression model may vary across the distribution. Instead, one contribution of this paper is to apply quantile analysis in order to map differentials across the entire distribution of wages from 1988 to 2008. This approach, 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 (2003) and Bishop, Luo, and Wang (2005). However, both these studies are restricted to comparing the urban labor markets in 1988 and 1995, based on the Chinese Household Income Project surveys (CHIPS). This paper goes further by extending the analysis to cover CHIPS data up to 2008.

A second contribution of our paper is to use the results of the quantile analysis to formally decompose changes in earnings inequality from 1988 to 2008 using the method of Machado and Mata (2005). This technique attributes changes in inequality into two broad sources. The first is changes in the wage structure—the coefficients of the quantile regressions. The second is changes in the covariates determining earnings—i.e., worker 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. Our paper is similar in objectives to a study by Xing and Li (2012), who look at residual wage inequality in China using CHIPS data from 1995 to 2007. We differ in starting from 1988 and by focusing on the Machado and Mata (2005) method, rather than the alternative DiNardo et al. (1996) decomposition. To anticipate our findings, both decomposition methods agree in attributing most of the rise in urban wage inequality in China to changes in the wage structure rather than to changes in the covariates of wages. However, beyond corroborating an existing finding in the literature, our decomposition goes further in disaggregating the changes in the wage structure into the effects of changes in the returns to specific worker and job characteristics.

The rest of the paper is structured as follows. Section 2 provides background, first providing an analytical framework for understanding wage differentials and then describing the institutional changes that occurred in China during the three sub-periods between the surveys. Section 3 introduces the data and econometric methods. Section 4 gives the result of the quantile analysis, focusing on how the returns to various observed worker characteristics changed in the period and how that varied across the conditional wage distribution. Section 5 presents the decomposition of wage inequality using the Machado–Mata method. Section 6 summarizes and concludes.

2. BACKGROUND

(a) *Analytical framework*

There are several potential broad explanations for the rise in wage inequality in China—notably, capital accumulation, skill

* We thank Economic and Social Research Council (ESRC, UK) for Grant support (Reference Number: ES/1035079/1); and Ford Foundation for the support of data collection and financial assistance. Final revision accepted: April 12, 2014.

biased technological progress, rural–urban migration, and the transition from a command to market economy. We briefly discuss these explanations—and any contrary equalizing forces—before turning to look in more detail at the specific institutional and policy changes within China during the period that may have played a role.

Much of the literature on wage inequalities starts from the premise that these reflect skill premia (see Acemoglu, 2002). While some skills may be proxied by observable worker characteristics such as education, others may be unobserved. Over time, the returns to skills may change due to changes in complementary factors or technology. Physical capital is typically thought to be more complementary to skilled labor than unskilled labor. China's exceptional economic growth has been driven in part by extremely high rates of investment in physical capital (for example, gross fixed capital formation rose from 31% of GDP in 1988 to 41% in 2007). Consequently, this accumulation of physical capital may be one factor behind the rise in wage inequality in China—an effect that will be amplified to the extent that capital goods embody skill-biased technical change.

The debate on the causes of rising wage inequalities in countries such as the US and the UK in recent decades has focussed on technology and trade as rival explanations for a rise in the price of skills. Technological progress such as computerization has been characterized as "skill-biased", complementing the productivity of skilled workers more than unskilled ones. Increased international trade may also benefit skilled workers in the West, following the Heckscher Ohlin theory. While the skill-biased technological change story may also apply to China, the Heckscher–Ohlin theory has the opposite implications for China to those for the West. Being abundant in unskilled labor, increased trade should reduce the premium enjoyed by skilled workers according to the simple theory (Chinese exports increased from 15% of GDP in 1988 to 35% in 2008). However, in practice, this effect of increased trade is complicated by the fact that openness is an important route for technological innovation in China. It allows imports of capital goods that embody advanced technologies and is associated with increased foreign direct investment, which may also transfer technology.

While skilled workers in urban China may have benefited more from technical change, they are also more likely to have protected been from competition from rural–urban migration. Since rural–urban migrants tend to be less educated than urban residents, they will have exerted more of a downward pressure on the wages of less skilled urban workers than on the wages of skilled workers. Many of the jobs of skilled workers are still effectively closed to rural–urban migrants, having a requirement of an urban household registration (*hukou*). Educational expansion may have served as a contrary supply side change, reducing the scarcity value of skills, but—as will be explained below—this may have been confined to the later part of the period under study.

The increase in rural–urban migration in China in the period in part reflects an institutional change: the reduction in official restrictions on labor mobility for rural households. There have been several other such changes during China's transition from a planned economy since 1978 which are likely to have influenced wage determination. Since planned economies are run on egalitarian Marxist principles, transitions to market-oriented economic systems are often expected to be disequalizing. In general, it has been argued that the transition from a planned economy to a market one will see a rise in the remuneration of productive characteristics and a fall in the importance of non-productive ones (Nee, 1989). The economic forces affecting the returns to skills will come to predominate in setting wages and so the wages paid by profit-maximizing firms will vary more than under administratively set pay schemes. However, there are at least two caveats to this general presumption. First, in China, the initial urban enterprise reforms gave managers of state-owned enterprises the freedom to vary the earnings of their employees through bonuses. In practice what this tended to mean was that the enterprise profitability became a major determinant of wages, contrary to the predictions of a competitive labor market. Within firms, bonuses were often allocated equally, an allocation likely to have been seen as equitable by workers given prevailing egalitarian beliefs and thus perhaps reflecting a managerial preference for a quiet life. Indeed, a rent-sharing model of wage determination seems at least as plausible in the Chinese context as a competitive one. Second, the market may allow an increase in wage discrimination by observed characteristics that are not *prima facie* productive, such as gender. Moreover, in the process of transition, the labor market may come to be more segmented. For example, certain industries or occupations may be effectively protected from entry by rural–urban migrants. In the next section, we describe in more detail the institutional changes in China during the period and how they are likely to have affected urban wage inequality.

(b) *Institutional changes in China, 1988–2008*

Given that our data consist of cross-sectional surveys taken in 1988, 1995, 2002, and 2008, it is useful to consider the major changes that took place in each of the three sub-periods between the surveys. The surveys were timed to give fairly equal intervals between them and to some extent align with notable changes in the Chinese economy and, to some extent, political leadership.

The first sub-period, from 1988 to 1995, can be characterized as the transition of a socialist economy from an administered system of wages to one with more competition but still within the framework of state ownership. In 1988, it can be questioned whether a labor market even existed in urban China (Knight & Song, 2005). Most workers were centrally allocated to their employment, basic wages were administratively determined, job security was guaranteed and there was almost no labor mobility. There was virtually no private employment in 1988, so it cannot be presumed that employers set wages competitively to reflect labor productivity. However, while there was minimal labor market competition, there was growing product market competition. Growing out of the plan, state-owned enterprises firms could more freely compete with each other and also faced a challenge from the low-cost rural enterprise sector that had emerged in the 1980s (Naugton, 1996). Moreover competition was no longer restricted to domestic markets, with the onset of trade liberalization after Deng Xiaou Ping's "southern tour" in 1992. This increased product market competition is likely to have affected wage determination due to the freedom already given to managers in the 1990s to set worker remuneration. This often took the form of paying bonuses on top of basic salaries. As in rent-sharing models of wage determination, workers in firms with profits could expect to share in this good fortune, but an increasing number of SOEs were becoming loss-making and so received no bonuses. Increased wage inequality in the period may therefore have partly been a reflection of increased variation in firm performance.

The second sub-period, 1995–2002, can be characterized as a period of retrenchment within the urban state sector, as it coincides with the period of radical urban reforms known as *xiagang* under the premiership of Zhu Rhongji (1998–2003). Falling profitability in the state-owned sector led to a mass retrenchment program, breaking the "iron rice bowl" of job security in the state sector and creating space for the emergence of a private sector. By the end of 2003, the number of the retrenched workers reached 28.18 million (News Office of the State Council, 2004). In other words, roughly one-fourth of SOE workers were retrenched. Not all workers were equally at risk of retrenchment—some, for example, older workers and women—were significantly more likely to be laid off than others (Appleton, Knight, Song, & Xia, 2002). The threat of redundancy is one factor influencing wages under a rent-sharing model; moderating the wages of those workers who are more at risk of being laid off. At the same time, some urban workers also started to face more competition from rural–urban migrants. Starting in 1992, strict controls on rural–urban migration were gradually relaxed, with the result that the number of rural urban migrants rose from an estimated 15 million in 1990 to 145 million in 2009 (NSB, 2011), accounting for roughly a third of urban employment. As noted in Section 2a, this increased rural–urban migration is likely to have increased wage inequality within urban residents. Since migrants tended to be less educated and were still segmented into specific occupations, some urban workers were more exposed to competition; for example, those in low skill retail or service occupations (Appleton, Knight, Song, & Xia, 2004).

The third sub-period, 2002–08, can be characterized as one of increased privatization. A significant private sector had already started to emerge, as urban workers responded to retrenchment of the late 1990s by turning to the non-state sector. As a consequence, the share of employment in state-owned enterprises started to fall, a trend that was accelerated after 2000 by the restructuring of firm ownership. For example, in our CHIPS data, less than 1% of workers in 1988 were employed in privately owned companies, rising to a fifth of workers in 2002 and over a third in 2008. [1] The period was also characterized by increased openness, coming just after China's accession to the WTO in 2001. Growth accelerated (from 8% to 10%) but the leadership of President Hu Jintao and premier Wen Jiabao (2003–13) sought to moderate the pursuit of growth with a concern for equity, under the slogan of "socialist harmonious society". This included a more tolerant attitude to rural–urban migrants, a concern for balanced development across the regions and the enforcement of minimum wages in cities. One feature of this period was a dramatic expansion in tertiary enrollment—the enrollment rate was increased by 40%, an initiative that started in 1999 but which only would have fed into the labor market from 2002 onward. Some argue that the period 2002–08 marks a retreat from reform, with the government strengthening state monopoly in some key sectors (such as infrastructure and banking) and re-instituting various price controls, although not on labor (Scissors, 2009). The end of the sub-period, 2008, marks the onset of the global financial crisis, leading to a slowdown in China's export growth.

3. DATA AND METHODS

(a) *Data*

We use four rounds of the urban household survey data conducted as part of the China Household Income Project, covering the years 1988, 1995, 2002, and 2008. The samples were randomly drawn from the larger annual national household income survey of the National Bureau of Statistics (NBS). 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. Our focus in this paper is on real wages, defined to include bonuses, price subsidies (which were important in 1988 before being largely withdrawn), regional allowances for working in mountainous areas, income in-kind, and income from secondary jobs. [2] Results from the surveys are reported in Griffin and Zhao (1993), Gustafsson, Li, and Sicular (2008), Li and Sato (2006), and Riskin, Zhao, and Li (2001).

In early rounds, the CHIP surveys sampled only households with urban registration (hukou). This restriction is common to almost all studies of the urban labor market in China, as the "floating population" of rural–urban migrants was not covered in urban household surveys by National Bureau of Statistics until 2003 and even now are not properly included in official sampling frames. [3] Consequently, for comparability across rounds, we focus on only households with urban hukou, excluding rural–urban migrant households because they are denied urban hukou status. For brevity, we often refer to urban wages and urban inequality when what is meant is the wages for registered urban residents and inequality among that population group. Analyzing urban residents as a population group is defensible 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. There have been comparisons of the wages of migrants and urban residents in urban China (see Appleton *et al.*, 2004; Meng *et al.*, 2010). These studies show that rural–urban migrants are paid significantly less than urban residents, having less education and being more concentrated in unattractive occupations—the so-called "3-Ds": dirty, dangerous, and disreputable. [4] Consequently, our figures for inequality are likely to under-estimate total urban inequality, inclusive of migrants. Since the proportion of rural–urban migrants has increased dramatically during the period, the rise in total urban inequality will be much larger than the rise in inequality among urban residents (although at a national level, migration may have exerted an equalizing effect). Rising urban–rural migration in China is likely to have had a depressing effect on their wages, due to the increase in the supply of urban labor. As noted in Section 2, the effect is likely to have been greater for certain groups of urban residents, for example, the less-skilled workers. It is thus one potential explanation of the rising inequality among urban residents.

Table 1 shows the general picture of a dramatic rise in inequality in urban wages from 1988 to 2008. Figure 1 illustrates this graphically by plotting the Lorenz curves for the four years. The curve for 1988 clearly dominates those for 1995 and 2002 (which are hard to separate) while these two in turn dominate that for 2008. The Gini coefficient—and all other indicators of inequality—increased markedly in the first interval, from 0.237 in 1988 to 0.345 in 1995. It was largely unchanged in 2002, standing at 0.348, but then rose sharply again to 0.45 in 2008. Thus over the twenty years, distribution of urban wages in China has gone from being relatively equal by international standards to being high. The 2008 estimate approaches levels as high as those reported for urban areas of Brazil in 2009 (Naticchioni & Cruz, 2012). By comparison, the Gini coefficient for wages in the US in the same period only ranged in the mid to low 30s, depending on the data source used (Lerman, 1997). Insight into the details of rise in wage inequality during the period can be gained from the ratios of high and low wage percentile point values: for

Table 1. *Urban wage inequality*

	1988	1995	2002	2008
Percentile ratios				
p90/p10	2.82	5.04	4.96	6.43
p75/p25	1.65	2.17	2.29	2.59
p90/p50	1.57	1.99	2.08	2.63
P50/p10	1.80	2.54	2.38	2.45
Skewness	7.16	11.09	4.32	10.62
QSK 595%	0.47	1.03	1.46	2.71
QSK 10–90%	0.28	0.63	0.87	1.76
QSK 25–75%	0.12	0.30	0.26	0.56
Gini coefficient	0.237	0.345	0.348	0.450
General entropy				
GE(−1)	0.238	0.576	0.286	0.420
GE(0)	0.108	0.235	0.212	0.347
GE(1)	0.108	0.226	0.215	0.440
GE(2)	0.148	0.379	0.297	1.126
Atkinson index				
A(0.5)	0.051	0.106	0.101	0.175
A(1)	0.102	0.210	0.191	0.293
A(2)	0.322	0.535	0.364	0.457
No. of observations	17733	12245	10133	6947

Sources: Calculated from the CHIP 1988, 1995, 2002, and 2008 urban household surveys.
The measure of quantile-based skewness (QSK) is a ratio of the upper spread to the lower spread minus one: $\mathrm{QSK}^{(p)} = \left[(Q^{(1-p)} - Q^{(.5)})/(Q^{(.5)} - Q^{(p)})\right] - 1$ for $p < 0.5$. The quantity $\mathrm{QSK}^{(p)}$ is re-centered using subtraction of one, so that it takes the value zero for a symmetric distribution. A value greater than zero indicates right-skewness and a value less than zero indicates left-skewness.

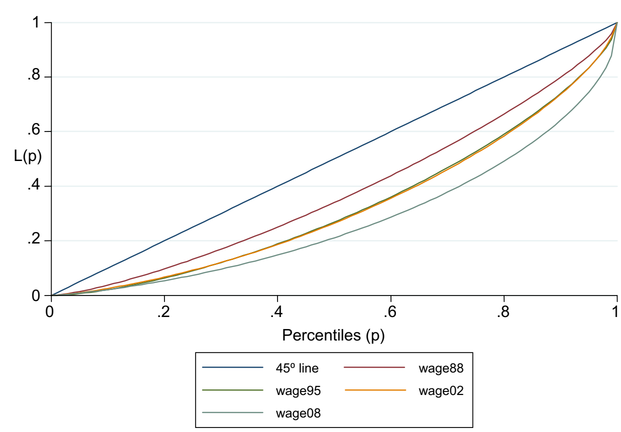

Figure 1. *Lorenz curves of wages in urban China 1988–2008.*

example, the ratio of the 90th to 10th percentile soared from 2.82 in 1988 to 6.43 in 2008.

In modeling wages, our explanatory variables are divided into worker characteristics and job characteristics, with an additional set of dummy variables for provinces. Among the worker characteristics, we identify two productive characteristics, commonly thought to proxy human capita: education in years and years of experience, the latter being entered as a quadratic.[5] Other worker characteristics—sex, Communist Party membership, non-Han Chinese ethnicity—are controlled for as non-productive characteristics as *prima facie* they do not seem likely to directly affect productivity.

Among job characteristics, we distinguish the ownership sector of the enterprise the worker is employed in (state-owned enterprise, privately owned, etc.). This is to identify changes of inequality between state-ownership and other ownership sectors. In addition, occupation has been employed as one of the explanatory variables in order to identify wage gaps between skilled professional and low-skilled workers. We also control for different industrial sectors. The means of our explanatory variables are given in Table 2, and discussion of the trends is presented in Section 4.

(b) *Method*

Let $Q_\theta\,(w_{it}|X_{it})$ for $\theta\epsilon(0,1)$ 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:

$$Q_\theta\left(w_{it} : X_{it}\right) = X'_{it}\beta_t(\theta) \tag{1}$$

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 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.[6] Afterward, we plot a curve for the 1,000 coefficients on a given explanatory variable against the 1,000 quantile points for each year (see Figures 2–11). 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.[7] 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

Table 2. *Personal and job characteristics of the workers (%)*

	1988	1995	2002	2008
Male	52.23	52.58	55.55	56.23
CP members	23.47	24.51	28.81	n.a.
Minority	3.77	4.30	4.10	1.11%
Education in years	10.04	10.73	11.46	10.50
Age in years	37.10	38.56	40.45	39.00
Experience in years	21.06	21.83	22.99	22.50
Ownership structure				
SOEs	77.67	79.04	64.76	49.59
Urban collective	20.28	15.06	6.86	5.30
Private ownership	0.77	1.65	20.72	33.81
Foreign-owned or joint venture	0.36	1.27	2.17	6.90
Other ownership	0.92	2.98	5.49	4.40
Occupation				
Private business owners	1.21	1.47	4.63	8.67
White collar	45.42	52.83	51.63	51.19
Blue collar	52.76	37.44	40.47	34.00
Other occupations	0.60	8.26	3.27	6.15
Industrial sectors				
Primary	4.13	2.65	2.78	1.60
Manufacturing	42.72	39.86	24.96	16.80
Construction	3.41	2.87	3.23	3.89
Transportation and comm.	6.74	4.86	7.77	13.19
Wholesale and retail	14.41	14.23	12.20	20.50
Public utilities and real estate	2.45	3.81	14.65	16.53
Social welfare	4.55	4.39	5.07	6.55
Education and media	7.21	7.11	8.96	5.43
Sciences and research	2.89	2.27	2.56	2.36
Financial sector	1.53	1.92	2.67	3.60
Government	8.42	11.32	11.91	9.31
Other industries	1.52	4.71	3.25	0.26

Sources: Calculated from the CHIP 1988, 1995, 2002 and 2008 urban household survey.

distribution. The quantile approach recognizes 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 the 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 favorable unobserved determinants of wages. This form of words reveals 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 labeled "ability" in the theoretical literature (although they may also encompass determination, ambition, and factors such as personal appearance). For example, we may have 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 Eq. (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:

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

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:

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

Along the lines 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,

$$\alpha(f^*(w(0); \beta_i(1))) - \alpha(f^*(w(0))) \quad (4)$$

where $f^*(w(0); \beta_i(1))$ 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. 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).

4. RESULTS FROM QUANTILE REGRESSIONS

Figures 2–11 present the coefficients from quantile regressions for wages in 1988, 1995, 2002, and 2008.

(a) *Wage gaps by 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.

Figure 2 shows that, while returns to education rose in urban China from 1988 up to 2002, they then fell somewhat during 2002–08. As discussed in the analytical framework, one might expect an increase in the returns to education during the transition from a command economy to a market based one. Rises in returns to education have been previously reported in China in the 1990s (Appleton, Song, & Xia, 2005; Zhang, Zhao, Park, & Song, 2005) and in other transitions, such as those in Eastern Europe (Svejnar, 1999). However, the fall in returns from 2002 to 2008 bucks this trend and suggests that the rise in wage inequality is not attributable to increased returns to education. The explanation for the fall in the returns to education may lie in the marked expansion of tertiary education starting in 1999 noted above in Section 2b, which reduced its the scarcity value in the following decade. [8].

The pattern of returns to education across the quantiles has also changed over time. In 1988 and particularly in 1995, the returns fell as the quantile rose, as has been observed in previ-

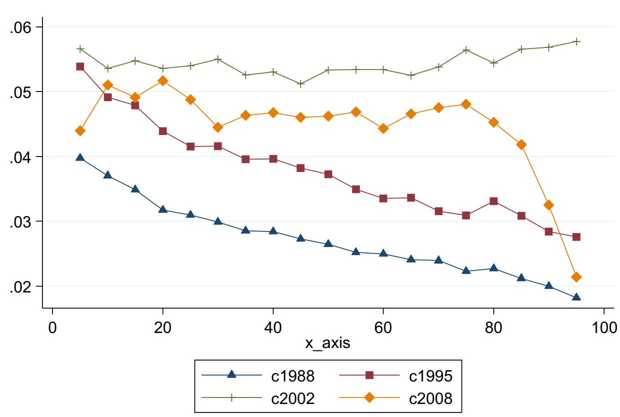

Figure 2. *Return to school years.*

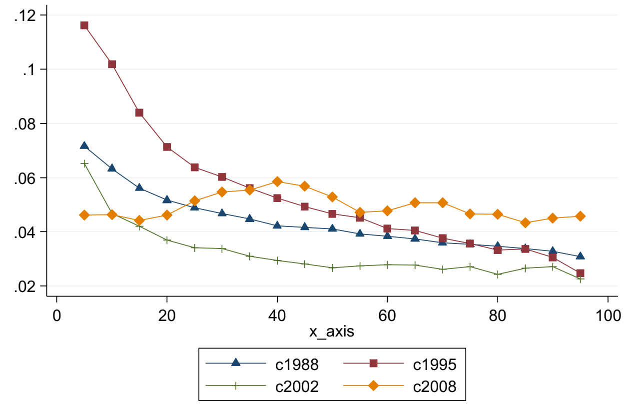

Figure 3. *Return to experience.*

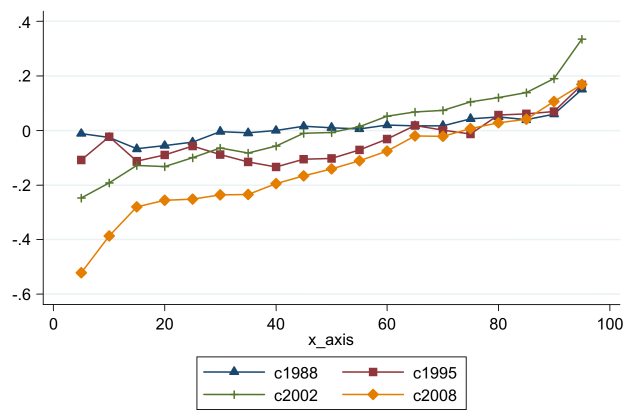

Figure 4. *Wage gap of firm owners vs white collar.*

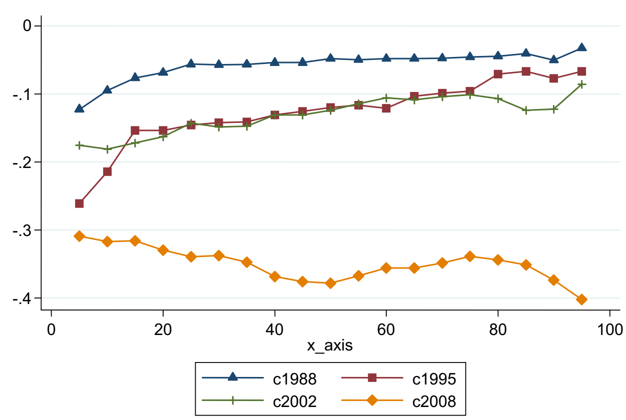

Figure 5. *Wage gap of blue collar vs white collar.*

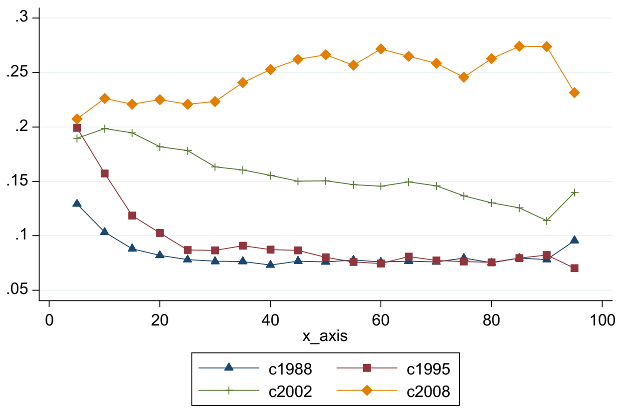

Figure 6. *Wage gap of male vs female.*

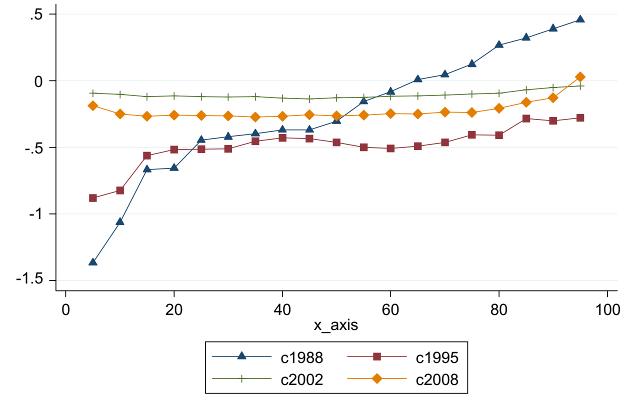

Figure 9. *Wage gap of private firms vs SOEs.*

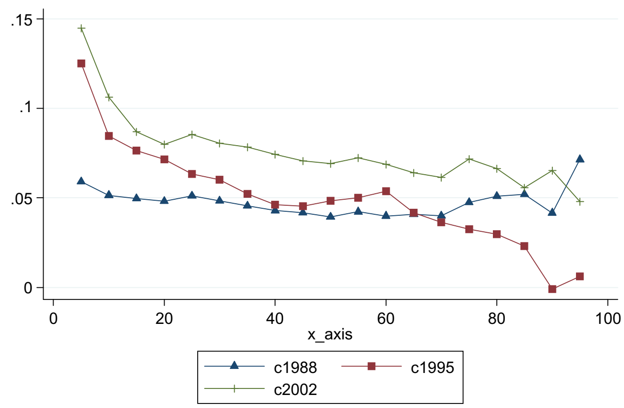

Figure 7. *Wage premium to Communist Party members 1988–2002.*

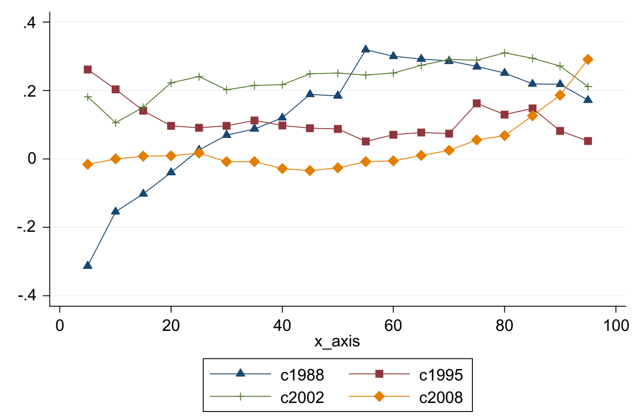

Figure 10. *Wage gap of foreign firms vs SOEs.*

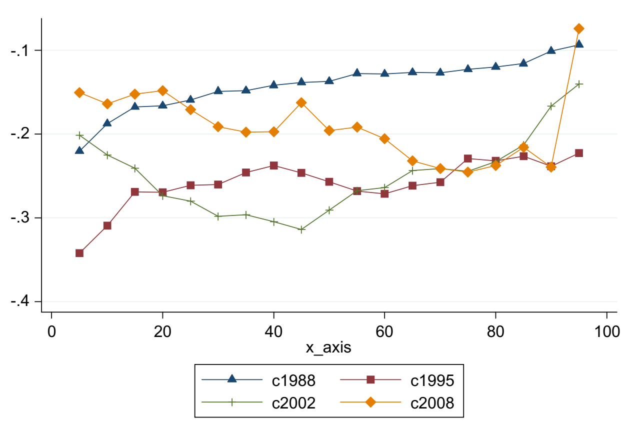

Figure 8. *Wage gap of collective firms vs SOEs.*

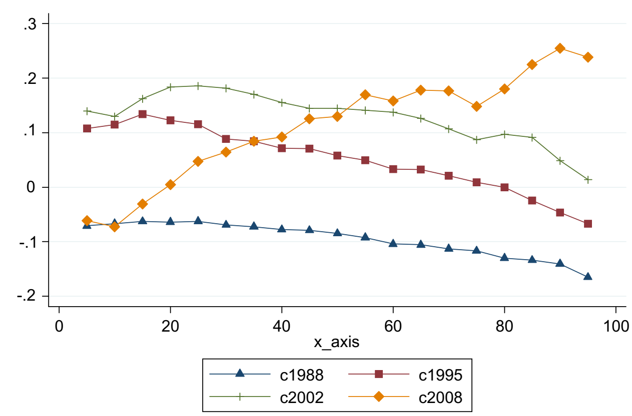

Figure 11. *Wage gap of civil servants vs manufacturing.*

ous quantile regression analyses of wages in urban China (Bishop *et al.*, 2005; Knight & Song, 2003). By contrast in 2002, the returns to education are fairly uniform across the distribution, lying in the 5–6% range. In 2008, the returns are fairly constant for most of the distribution, but then collapse at the upper end.

What might explain the tendency for returns to education to be lower at the upper quantiles? The pattern contradicts the common assumption that education complements unobserved worker ability. This assumption was invoked by Buchinsky (1994) to account for the pattern of returns rising at upper quantiles found in his pioneering analysis of wages in the US. 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 (2003) 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, total wages, inclusive of bonuses, might be expected to vary more with education at the lower end of the distribution than at the top. This explanation may not be applicable to 2002, because that year comes toward the end of the period of radical urban reform and retrenchment in SOEs. Profitability in SOEs had fallen dramatically, so that profit-related bonuses were less significant. What remains puzzling is why returns to education appear to plummet for the top end of the distribution during 2002–08. One explanation which cannot be tested with our data is that some high paid jobs could be obtained via bribery or using personal connections; a phenomenon commonly noticed and reported by the media in the past decade. This would show up in our decompositions as a positive unobservable effect, but may not be related to education. Another explanation could be that high paid jobs are mostly in owner-occupied firms, managerial or administrative posts in the state sector for which education is not the best measure of human capital: other unobserved skills or talents may be more important.

Experience is the other productive characteristic whose return might be expected to rise in transition.[9] Abstracting from 2002, the returns to experience generally rise at the median during the period (Figure 3 refers). However, in 2002, the year after the period of mass urban retrenchment, the returns to experience are markedly lower than in other years. It should be noted that more experienced workers were more at risk of being laid off (Appleton *et al.*, 2005): this implicit threat of redundancy may have exerted a downward pressure on their wages. By 2008, this threat had been lifted and so the returns to experience rose.

Looking at the pattern of the returns to experience across the quartiles, there is some similarity with the pattern of the returns to education. In 1988 and particularly in 1995, the returns appear to fall with the quartile. This is contrary to what one might expect in a market economy: Mincer (1974) predicted wage inequalities would rise with experience as a consequence of increased variation in on the job training or learning. However, it may be explained, as argued with education, by the existence of fewer bonuses at the lower end of the distribution, given that bonuses tended to be shared quite equally without regard to seniority. It might also be that it was older workers with less favorable unobserved personal characteristics (lower "ability") that tended to benefit more from seniority under administered pay scales. By 2008, the returns to experience do not vary systematically across the distribution. Consequently, comparing the first and last round of the surveys, the returns to experience are lower in 2008 than 1988 for the bottom fifth of the distribution but higher for the rest. For both education and experience, therefore, there has been some tendency for returns to rise during transition and to become flatter across the quartiles.

(b) *Wage gaps between occupations*

Wage differentials by occupation have increased during the period. We distinguish three broad occupational categories: white collar workers (our default category); private business owners; and blue collar workers. White collar workers include professional or technical workers, managers, department heads, and clerks while blue collar workers are manual workers.

Figure 4 shows the wage gap between private business owners and white collar workers was almost indiscernible in 1988. However, the gap widens over time, particularly pronounced for lower quartiles in 2008. This may reflect an increasing heterogeneity among private business owners. At the lower end, they will have faced increasing competition from migrants (most of whom are self-employed) from which white collar workers have been largely insulated (since few white collar jobs are open to migrants).

There has also been a widening gap between the earnings of white collar and blue collar workers, again being most pronounced during 2002–08 (Figure 5 refers). In 1988, the wage gap was less than 1% except for the very lowest paid. By 2008, the gap was around 3–4%. During 2002–08, the gap increased most at the upper end—widening by around three percentage points—and least at the lower end—where the increase was little more than one percentage point. This may be partly a consequence of skill biased technical change, with white collar workers' productivity benefiting more from improvements in ICT. It may be that the onset of the global credit crunch and the slow-down in exporting had a more pronounced negative impact on the better paid blue collar workers who tend to be employed in export industries.

(c) *Wage gaps by unproductive characteristics of workers*

During the period, there has been a marked rise in the pure gender gap in wages in urban China (Figure 6 refers). This has sometimes been observed in other countries' transitions from communism, but is far from being a universal feature.[10] There have been numerous studies of the rising gender wage gap during China's transition—see, for example, Ng (2007) and Chi and Li (2007). We find no marked change at the median quartile from 1988 to 1995, but then the gap widens greatly in both the later intervals, 1995–2002 and 2002–08. Women experienced a higher risk of retrenchment after 1995 (Appleton *et al.*, 2002), so it is possible that this had a moderating effect on their wages.[11] Moreover, the gender gap among retrenched workers who found new employment was much more pronounced than among those who escaped retrenchment (Appleton *et al.*, 2004). Historically, pay scales appear to have been fairly equal between men and women in China. Retrenchment in 1995–2002 and increased privatization thereafter may have given employers more freedom to pay women less than men. Ng (2007) found the gender wage gap during 1987–2004 rose faster in provinces that grew faster, surmising these areas may also have deregulated wages faster. Numerous studies of the gender wage gap by ownership, have found the gap greater in private enterprises than state-owned or collective enterprises (see, for example, Zhang & Dong, 2008). We do not have data on productivity, so cannot determine whether the transition allowed employers to pay women less than men because women were less productive or because of managers' prejudice against women.

The gender wage gap has tended to rise more for workers higher up the conditional wage distribution. This partly reflects the fact that the wage gap at the start of the period (1988) and particularly in 1995 was already substantial for lower paid workers. This phenomenon of a higher gender wage gap for the lower paid has been termed a "sticky floor" (in contrast to the "glass ceiling" that may apply at the top end of the wage distribution). As shown in Figure 6, the gap in 1988 and 1995 has an "L-shape", being much higher at the very bottom of the distribution. The gap shifts up in 2002 and becomes flatter, but retains a negative slope. Our results for 1988, 1995, and 2002 mirror those found on different data for 1987, 1996, and 2004 by Chi and Li (2007, see their Figure 3). However, our finding for 2008 is markedly different from those for earlier years. We find in the last interval, from

2002 to 2008, the gap increases more as we move up the wage distribution and the pattern for 2008 is positively sloped. This is more consistent with a "glass ceiling" effect and contrary to the negative "sticky floor" finding for earlier years.

Figure 7 plots the wage premium for Communist Party membership across the conditional wage distribution for the first three rounds of the survey: unfortunately, the last round did not record respondents' party membership. Like the pure gender gap, the CP wage premium rises during transition and is *prima facie* evidence of the deregulated labor market discriminating more according to unproductive characteristics (see Appleton, Knight, Song, & Xia, 2009). It is sometimes argued that CP membership signals high underlying productivity and this—rather than any discrimination in favor of party members—explains the wage premium (Li, Liu, Ma, & Zhang, 2007).[12] 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 *et al.* (2005) suggest that party membership plays a particular role in signaling ability among low earnings workers who typically lack the educational certificates more conventionally thought to signal ability.

(d) *Wage gaps by ownership structure*

Section 2b noted the declining share of employment in state-owned enterprises (SOEs) and in collective firms. Figure 8 shows a widening gap over time between pay in SOEs and collective firms, *ceteris paribus*, at least after the first quartile. Very few workers were employed in private or foreign firms in 1988, but the results in Figures 9 and 10 suggest that the gap between pay in those firms and in SOEs varied markedly across the wage distribution. For higher quantiles, private and foreign-owned firms paid more than SOEs while at lower quantiles, they paid less. By 2002 and 2008, the differentials had flattened out and no longer varied markedly across the quantiles. This suggests that in 1988, lower paid workers may have preferred employment in SOEs, where they would have enjoyed a wage premium, but higher skilled workers were better rewarded elsewhere. However, by 2008, 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 closer match to the patterns observed in private and foreign-owned/joint venture firms. It is notable that pay in SOEs rises somewhat relative to both private and foreign firms during 2002–08, a period in which—as noted in Section 2b—the government has been accused of protecting key large SOEs.

(e) *Wage gaps between industrial sectors*

Our models also estimated wage gaps between 12 different industrial sectors.[13] For brevity, we do not report the results in detail here. However, Figure 11, depicting the gap between civil servants and manufacturing workers is representative of some of the key results. In 1988, in common with workers in most tertiary industries, civil servants were paid less than manufacturing workers in China, *ceteris paribus*, so the coefficients on a dummy for civil service membership are negative in 1988 (with manufacturing as the default industry). By 1995, this gap had been reversed. Generally, there was little variation in these effects across the quantiles except for 2008, when the gap rises sharply as we move up the quartile. Wage inequalities appear to have become much greater among civil servants than manufacturing workers. The wage gap between these two groups is the same in 1988 and 2008 among bottom 10%, but progressively widens as we move along the distribution—reaching more than 20% toward the end.

5. DECOMPOSING THE CHANGE IN WAGE INEQUALITY

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 investigate the impact of changes in the covariates (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 those covariates.

Table 3 reports the results of decomposing the Gini index for wages using three intervals between the CHIP survey rounds. As shown in Table 1 and discussed in Section 2, wage inequality increased during the period with the Gini index rising from 0.237 in 1988 to 0.45 in 2008. The rise in the Gini index for wages was fairly equally divided between the first interval, 1988–95 and the last, 2002–08; it did not change appreciably in the middle interval, 1995–2002. Table 3 shows that most of the rise in wage inequality was attributable to changes in the wage structure—to the changes in coefficients discussed previously in Section 3. Changes in the covariates had no aggregate effect on inequality from 1988 to 1995 and accounted for only 0.016 (16%) of the 0.102 rise in the Gini index from 2002 to 2008. Changes in the covariates also implied a slight increase in inequality in 1995–2002, but this was largely offset by a negative residual in the decomposition. To understand these results more fully, we consider the contribution of specific factors to the decomposition, beginning with the productive characteristics of workers.

(a) *Changes in inequality and worker characteristics*

Changes in wage differentials by education are often thought to be key drivers of changes in inequality. However, the pattern in urban China varies over each of the three survey intervals. From 1988 to 1995, as shown in Figure 2, the returns to education shifted upward across the distribution with somewhat larger increases at the bottom. Consequently, this did not contribute to the rise in inequality. By contrast, from 1995 to 2002, the increase in returns to education was much larger at the upper end of the conditional distribution. The decomposition implies that this would have increased the Gini coefficient by 0.034. From 2002 to 2008, returns fell across the board but plummeted for the highest paid workers and hence the decomposition implies, *ceteris paribus*, this would have reduced the Gini coefficient by 0.06. Changes in the amount of education, as opposed to their returns, tended to lower inequality in all three intervals but these effects were modest.

Changes in the returns to experience had qualitatively similar effects to changes in the returns to education. Less well paid workers gained the most from the initial rise in returns to experience from 1988 to 1995, which would have reduced inequality. Conversely, they were hardest hit by the fall in returns to experience from 1995 to 2002—a trend which,

Table 3. *Decomposition of the changes in the wage distribution (start years used as base years)*

	1988–95	1995–2002	2002–08
Change in Gini	0.108	0.003	0.102
Aggregate contributions to the change in Gini			
Covariates	**0.000**	**0.013**	**0.016**
	(−0.013, 0.021)	(−0.005, 0.040)	(−0.018, 0.003)
Coefficients	**0.121**	**0.002**	**0.092**
	(0.111, 0.135)	(−0.009, 0.010)	(0.075, 0.116)
Residual	**−0.013**	**−0.012**	**−0.006**
Contribution of covariates to change in Gini			
Sex	**−0.002**	**−0.002**	**−0.001**
	(−0.006, 0.000)	(−0.006, 0.003)	(−0.004, 0.003)
CP membership	**−0.003**	**−0.002**	**N.A.**
	(−0.004, −0.001)	(−0.003, 0.000)	
Minority	**0.000**	**0.000**	**0.000**
	(0.000, 0.001)	(−0.001, 0.005)	(0.000, 0.000)
Education	**−0.001**	**−0.005**	**−0.009**
	(−0.005, 0.003)	(−0.010, 0.005)	(−0.018, −0.003)
Experience	**−0.003**	**−0.002**	**0.007**
	(−0.007, −0.004)	(−0.010, 0.006)	(0.004, 0.010)
Occupation	**0.000**	**0.001**	**0.005**
	(−0.005, 0.005)	(−0.007, 0.020)	(−0.003, 0.013)
Ownership	**0.000**	**0.012**	**0.000**
	(−0.006, 0.003)	(0.007, 0.018)	(−0.017, 0.012)
Industrial sector	**0.001**	**−0.001**	**0.001**
	(−0.008, 0.009)	(−0.008, 0.005)	(−0.004, 0.010)
Provinces	**−0.003**	**0.002**	**0.006**
	(−0.012,0.010)	(−0.013, 0.024)	(−0.015, 0.020)
Contribution of coefficients to the change in Gini			
Sex	**−0.002**	**−0.000**	**0.017**
	(−0.003, 0.002)	(−0.002, 0.001)	(0.014, 0.019)
CP membership	**−0.004**	**0.003**	**N.A.**
	(−0.006, −0.002)	(0.002, 0.003)	
Minority	**0.001**	**−0.001**	**0.000**
	(0.000, 0.005)	(−0.002, 0.000)	(0.000, 0.001)
Education	**−0.002**	**0.034**	**−0.060**
	(−0.004, 0.001)	(−0.030, 0.040)	(−0.063, −0.054)
Experience	**−0.019**	**0.041**	**−0.013**
	(−0.022, −0.016)	(0.037, 0.044)	(0.009, 0.020)
Occupation	**0.012**	**−0.003**	**0.009**
	(0.011, 0.015)	(−0.004, −0.002)	(0.003, 0.012)
Ownership	**0.003**	**0.001**	**0.018**
	(0.000, 0.005)	(−0.001, 0.005)	(0.009, 0.033)
Industrial sector	**0.003**	**0.011**	**0.026**
	(−0.008, 0.011)	(0.006, 0.026)	(0.018, 0.045)
Provinces	**0.016**	**−0.016**	**0.029**
	(0.009,0.025)	(−0.020, −0.011)	(0.016,0.35)

Note: (1) The change in the Gini coefficient is the mean of 10 times replication of the simulation with the coefficients from quantile regressions and 999 random samples drawn from the variable data sets with replacement. During each simulation, once the random samples are drawn, they will be used throughout the simulation. (2) Average values in bold. The maximum and minimum values of the 10 times replication are shown in brackets.

ceteris paribus, would have increased the Gini coefficient by 0.041. Rises in the returns to experience from 2002 to 2008 were greatest for the higher quartiles, further increasing inequality. The gradual aging of the workforce, and associated increase in its experience, tended to slightly reduce inequality in the first two intervals—during which the returns to experience were higher for the lower quartiles—but then increase it from 2002 to 2008.

Now we look at other personal factors such as sex, Communist Party (CP) membership and minority status. While the increased gender wage gap has worsened inequality between men and women, its impact on overall inequality over time is nuanced. It is only in the last interval, 2002 to 2008, that it appears to have markedly increased the Gini coefficient—implying an increase of 0.017, which accounts for 17% of the overall rise in inequality. Figure 5 suggests that this is because the rise in the gender gap in the earlier two intervals was greater at the lower end of the wage distribution. By contrast, from 2002 to 2008, the gap changes little at the bottom end but increases greatly for higher quartiles.

The rise in the Communist Party wage premium has not markedly affected overall wage inequality. The decomposition shows a small negative effect on the Gini in 1988–95, as the rise was greater at the lower end of the distribution and indeed the premium fell for the top third of workers. But this was almost entirely reversed in 1995–2002. Changes in the wage gap of minority workers relative to Han Chinese workers have also not had an appreciable effect on the Gini coefficient.

(b) *Changes in inequality and job characteristics*

Table 2 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 in covariates on inequality to be rather modest. It is only in the middle interval, 1995–2002, that there is a discernible effect: implying an increase of 0.012 in the Gini coefficient. Changes in wage differentials by ownership initially had little impact on the change in inequality, but did contribute to rising inequality in the final period—accounting for an estimated 18% of the overall rise from 2002 to 2008.

The widening wage gap between blue and white collar workers also contributed to the rise in inequality. During the first interval, 1988–95, it implied a 0.012 increase in the Gini coefficient (11% of the overall rise). There was no change in the wage gap from 1995 to 2002 but in the last period, 2002–08, a further increase in this occupational wage gap accounted for about 9% of the rise in inequality in this period.

Changes in wage differentials by industry also tended to raise overall inequality. The effects were small from 1988 to 1995, but rose thereafter. In 1995–2002, they increased the Gini by 0.011 *ceteris paribus;* in 2002–08, the contribution rose further to 0.026, a full quarter of the overall increase in the inequality. Figure 11, on the wage gap between civil servants and manufacturing workers provides some insight into this. In 2002, the gap was fairly even across the distribution, falling somewhat as we move up the quantiles. By contrast, in 2008, the gap sharply rises as we move up the distribution and thus worsens inequality.

6. CONCLUSIONS

This paper uses quantile analysis to make three broad contributions to the literature on the determinants of earnings and inequality in urban China. First, it updates the literature with results from the Chinese Household Income Project for the past decade. Second, it tracks the evolution of the wage differentials across the entire distribution of wages rather than merely focusing at the mean or median. Third, it identifies how these changes in the wage structure—and to a lesser extent the profile of employment—have led to rising inequality.

In terms of the first contribution, while the period 2002–08 has seen a renewal of the rise in wage inequality observed from 1988 to 1995, there have been some reversals in other trends. For example, the returns to education fell in this interval, as did the wages of workers in private and foreign-owned firms relative to those in state-owned enterprises. By contrast, the gender gap continued to rise, as did the gap between white collar and blue collar workers, and between manufacturing and most other industrial sectors.

As for the second contribution, tracking changes across the entire distribution of wages, it is clear that changes are seldom uniform for all quantiles, but are often complex and variable across the different survey intervals. This provides justification for the quantile regression based methods used here and the detailed examination of each survey year. Simplistic assumptions or generalizations rarely match the patterns observed in the data. For example, it is often assumed that returns to education rise with unobserved ability, but we find opposite that: returns to education were initially higher for those with unfavorable unobservables—the low quantiles. By 2002, this pattern has all but been eroded before showing signs of emerging again in 2008. The gender wage gap in the earlier surveys was larger for lower paid workers (consistent with the "sticky floor" characterization) but in 2008, was larger for higher paid workers (consistent with the "glass ceiling" archetype).

Finally, on the third contribution, the Machado and Mata decomposition suggests that changes in the wage structure have played the dominant role in explaining the rise in inequality in urban China. Changes in worker or job characteristics play a comparatively minor role. This conclusion corroborates the findings of Xing and Li (2012) who used the alternative DiNardo decomposition on the same CHIPS data (although spanning only 1995–2007). What our decomposition adds is a disaggregation of the changes of the wage structure into the impact of changes in the returns to different covariates. This is most successful for the latest period, 2002–08, when changes in the coefficients of many variables contribute sizably to the change in the Gini. Perhaps surprisingly, changes in the returns to education and experience have been equalizing, challenging the notion that rising inequality is a consequence of increased returns to skills due to skill-biased technical change or privatization. However, changes in every other category of observed wage differential have served to widened inequality. These widening differentials include (in decreasing order of importance): province, industry, ownership, gender, and occupation. The results of this paper suggest that the most recent (2002–08) rise in wage inequality among urban Chinese workers is due to a variety of widening wage gaps. It is not due to any one observable factor alone (e.g., changes in education or in the returns to education). Instead, it is due to unobserved factors, captured in the constants in the quantile regressions, and due to widening differentials by many observed characteristics. As such, given the Chinese government is concerned to limit the rise of inequality, it is not clear that intervention should be targeted on any one dimension. Instead, a more general response—for example, focusing on tax and benefit entitlements—would seem to be required.

NOTES

1. Conversely, the share of employment in SOEs falls in our data from over three quarters in 1988 and 1995 to less than a half in 2008. Employment in urban collectives also falls, from 20% in 1988 to 5% in 2008.

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.

3. The official urban household survey excluded those without urban hukou until 2003. In 2003, only 2% of individuals sampled live in households without urban hukou. This seems a gross under-estimate of the proportion of migrants in the urban labor market and probably reflects a failure to properly enumerate those living on the periphery of urban areas or in dorms or other workplaces such as construction strikes (Meng, Shen, & Xue, 2010) The CHIP surveys of 1999, 2002, and 2007–09 do sample migrants, but in the absence of an official sampling frame, these sub-samples may not be representative and are hard to assign population weights to.

4. 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.

5. Potential experience is measured as age in years minus (years of schooling plus six). We explore entering school years as a quadratic, but the squared term was usually insignificant.

6. The distance between any two quantile points is 0.001.

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

8. An anomalous feature of the CHIP survey data is that average years of education of urban workers falls slightly from 2002 to 2008 (see Table 2). We have no explanation for this anomaly which may indicate a sampling problem but the point remains that the expansion of educated labor at the national level should have had a moderating influence on the returns to education of those workers in the CHIP sample.

9. In fact, the returns to experience have often been observed to fall during transition—for example, during the East European transitions (Svejnar, 1999). This has been explained as a consequence of pre-reform administered wages over-rewarding seniority.

10. 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 and Reilly (2007) find a fall in the gap in Vietnam in the 1990s.

11. There may also have been selectivity effects, but one might expect these selectivity effects to *lower* the gender gap, as women with less favorable unobserved characteristics might have been more vulnerable to retrenchment.

12. A referee questions whether Communist Party membership should be included as an independent variable. It is true that it may be capturing unobserved characteristics rather than having a causal role. However, this could be said of all the explanatory variables in a conventional wage function (e.g., education) and it is not clear that the endogeneity bias is more severe with Party membership. Ultimately, wage functions capture wage differentials by observed characteristics and these are interesting in identifying patterns in the data, but care must be taken in interpreting their results.

13. There are (1) primary (including agriculture, forestry, herding, fishing, and mining); (2) manufacturing; (3) construction; (4) transportation and communication; (5) commerce (whole sale and retailing); (6) public utilities and real estate (water, gas and electricity supply, real estate, social service); (7) social welfare (health, sports, and the like); (8) education and media (education, culture and arts, broadcasting, film and television); (9) sciences and research (scientific research, water control, geological investigation); (10) financial sector; (11) government administration; (12) other not belonging to any sector listed above.

REFERENCES

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature, 40*, 7–72.

Appleton, S., Knight, J. B., Song, L., & Xia, Q. (2002). Urban retrenchment in China: Determinants and consequences. *China Economic Review, 13*(2/3), 252–275.

Appleton, S., Knight, J. B., Song, L., & Xia, Q. (2004). Contrasting paradigms: Segmentation and competitiveness in the formation of the chinese labor market. *Journal of Chinese Economics and Business Studies, 2*(3), 195–205.

Appleton, S., Knight, J. B., Song, L., & Xia, Q. (2009). The Economics of Communist Party membership in urban China. *Journal of Development Studies, 45*(2), 256–275.

Appleton, S., Song, L., & Xia, Q. (2005). Has China crossed the river? the evolution of wage structure in urban China during reform and retrenchment. *Journal of Comparative Economics, 33*(4), 644–663.

Bishop, J. A., Luo, F., & Wang, F. (2005). Economic transition, gender bias, and the distribution of earnings in China. *Economics of Transition, 13*(2), 239–259.

Buchinsky, M. (1994). Changes in the US wage structure 1963–1987: Application of quantile regression. *Econometrica, 62*(2), 405–458.

Chi, Wei, & Li, Bo (2007). Glass ceiling or sticky floor? Examining the gender earnings differential across the earnings distribution in urban China, 1987–2004. *Journal of Comparative Economics, 36*(2), 243–263.

Deaton, A. (1992). *The analysis of household surveys*. Baltimore: John Hopkins.

DiNardo, J., Fortin, N., & Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach. *Econometrica, 64*, 1001–1044.

Ge, S., & Yang, D. T. (2012). *Changes in China's wage structure* IZA discussion paper no. 6492. Bonn: IZA.

Griffin, K., & Zhao, R. (1993). *The distribution of income in China*. London: Macmillan and Co.

Gustafsson, B. A., Li, S., & Sicular, T. (2008). *Inequality and public policy in China*. New York: CUP.

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

Knight, J., & Song, L. (2005). *Towards a labour market in China*. Oxford: OUP.

Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica, 46*, 33–50.

Lerman, R. I. (1997). Reassessing trends in US earnings inequality. *Monthly Labor Review, 130*, 17–25.

Li, H., Liu, P. W., Ma, N., & Zhang, J. (2007). Economic returns to Communist Party membership: Evidence from Chinese twins. *Economic Journal, 117*(553), 1504–1520.

Li, S., & Sato, H. (2006). *Unemployment, inequality and poverty in urban China*. London and New York: Routledge Curzon.

Machado, J. A. F., & Mata, J. (2005). Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics, 20*(3), 445–465.

Meng, Xin, Shen, Kailing, & Xue, Sen (2010). *Economic reform, educational expansion, and earnings inequality for urban males in China, 1988–2007* IZA discussion paper 4919. Bonn: IZA.

Mincer, Jacob (1974). *Schooling, experience and earnings*. New York: NBER.

Naticchioni, P., & Cruz, B. O. (2012). *Falling urban wage premium and inequality trends: Evidence for Brazil*. mimeo, Brasília: Instituto de Pesquisa Econômica Aplicada – IPEA.

Naugton, Barry (1996). *Growing out of the plan: Chinese economic reform, 1978–1993*. Cambridge: CUP.

Nee, V. (1989). A theory of market transition: from redistribution to markets in state socialism. *American Sociological Review, 54*(5), 663–681.

Newell, A., & Reilly, B. (2001). The gender pay gap in the transition from communism: some empirical evidence. *Economic Systems, 25*(4), 287–304.

News Office of State Council, The White Paper on the Situation and Policies of Employment of China (zhong guo de jiu ye zhang kuang he zheng ce bai pi shu), Beijing: April 2004.

Ng, Y. C. (2007). Gender earnings differentials and regional economic development in urban China, 1988–97. *Review of Income and Wealth, 53*(1), 148–166.

NSB, 2011. National Bureau of Statistics of China Report 2011. Numbers, structure and characteristics of new generation rural–urban migrant workers in China. March 11, 2011.

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

Pham, T., & Reilly, B. (2007). The gender pay gap in Vietnam, 1993–2002: A quantile regression approach. *Journal of Asian Economics, 18*(5), 775–808.

Riskin, C., Zhao, R., & Li, S. (2001). *China's retreat from equality: Income distribution and economic transition*. Armonk, New York: M.E. Sharpe.

Scissors, Derek (2009). Deng undone: The costs of halting market reform in China. *Foreign Affairs, 88*(3), 24–39.

Svejnar, J. (1999). Labor markets in transitional central and east European economies. In O. Ashenfelter, & D. Card (Eds.). *Handbook of labor economics* (Vol. 3B, pp. 2809–2857). Amsterdam: Elseiver.

Xing, C., & Li, S. (2012). Residual wage inequality in urban China 1995–2007. *China Economic Review, 23*(2), 205–222.

Zhang, L., & Dong, X. (2008). Male–female wage discrimination in Chinese industry. *Economics of Transition, 16*(1), 85–112.

Zhang, J. S., Zhao, Y., Park, A., & Song, X. (2005). Economic returns to schooling in urban China, 1988–2001. *Journal of Comparative Economics, 33*(4), 730–752.