ISSN 2042-1850

CHINA GROWTH CENTRE (CGC) AT ST EDMUND HALL, UNIVERSITY OF OXFORD

CGC Discussion Paper Series

No. 18

February 2013

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Simon Appleton, Lina Song, Qingjie Xia

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Simon Appleton[a], Lina Song[b], Qingjie Xia[c]

JEL classification: J31; J42; O15; P23

Keywords: China, labour, wages, quantile regression, inequality

Corresponding author:

Lina Song
E-mail address: lina.song@nottingham.ac.uk

[a]School of Economics, University of Nottingham, NG7 2RD, U.K.
[b]School of Contemporary Chinese Studies, University of Nottingham, NG8 1BB, U.K.
[c]School of Economics, Peking University, Beijing, China 100871

Abstract

This paper examines change in wage gaps in urban China by estimating quantile regressions on CHIPS data. It applies the Machado and Mata (2005) decomposition, finding sharp increases in inequality from 1988 to 1995 and from 2002 to 2008 largely due to changes in the wage structure. The analysis reports how the returns to education and experience vary across wage quantiles, along with wage differentials by sex and party membership. The role of industrial structure, ownership reform and occupational change are also estimated. In the recent period, 2002 to 2008, falls in the returns to education and experience have been equalising. However, changes in every other category of observed wage differential - by sex, occupation, ownership, industrial sector and province – have served to widened inequality. 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.

Acknowledge

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.

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. Has China's spectacular economic growth been partly at the expense of widening inequality? Conventionally, rising income inequality in transitional economies has been viewed as a necessary trade-off for increased efficiency, with pre-reform China emphasising an egalitarian distribution of earnings the expense of incentives and rewards for private initiative. Yet widening inequality may destabilise the economy – fostering socio-political discontent from the "losers" and thereby engendering instability.

While the big picture of rising income inequality at the national level has been widely observed, a more in-depth and differentiated analysis of the contributors to income inequality across all income cohorts over time has so far been lacking. For example, economic reform has seen a widening gender wage gap on average, has this affected low income earners more than their higher income counterparts? Similar questions could be addressed concerning other factors such as ownership, industrial sectors, and individual's characteristics including education, occupation, seniority and party membership. Can income inequality be resulted in or reflecting such changes over time? Using quantile analysis on surveys of urban residents, this paper explores the answers covering the period between 1988 and 2008.

Wage earnings are the main source of income for urban Chinese residents. Whether wage is equality distributed affects the nature of the Chinese labour market, and hence the scale and degree of socio-political discontent. Therefore, in this paper, we focus on wage differentials among urban residents as one aspect of income inequality. There has been a marked increase in wage inequality during the period. For example, the ratio of the average wage of the highest paid industry to that of the lowest paid one increased from 1.76 in 1990 to 4.88 in 2005 (SCDR, 2007; Gu and Feng, 2008). Increasing wage differentials among urban residents have contributed to a national rise in inequality.

This paper focuses on the period 1988 to 2008. The past two decades saw the change of Chinese central leaderships and along with it, changes in policies. 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 relaxed at the same time and the number of rural urban migrants soared from 15 million in 1990 to 145 million in 2009 (NSB, 2011). 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

[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).

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). Under the leadership inaugurated in 2002, state monopoly in the certain profitable industries has been reinforced, and the private sector in general lost its competitive power. This was amplified with the global credit crunch that started in 2008 and reduced the demand for Chinese exports. The slowdown of China's exports might have contributed to income equality in the policy environment where state controlled investment to rescue the economy was largely focused on infrastructure and a weak domestic demand for consumption.

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). This paper goes further by extending the analysis to cover CHIPS data up to 2008. Our paper is similar in objectives to a study by Xing and Li (2012), who look at residual wage inequality in China from 1995. We differ in starting from 1988 and by focussing on the Machado and Mata (2005) method, rather than the alternative DiNario et al. (1996) decomposition. A related study is Ge and Yang (2012), who use alternative data - the Chinese Urban Household Surveys - to analyse changes in China's wage structure from 1992 to 2007.

Using the results of quantile analysis of wage differentials in four rounds of CHIP surveys spanning twenty years, 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 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 surveys were national representative, and 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 labour 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), Riskin et al. (2001), Li and Sato (2006) and Gustafsson, *et al*. (2008).

In most rounds, the CHIP surveys sampled only households with urban registration (*hukou*). Consequently, for comparability across rounds, we focus on only these households, excluding rural–urban migrant households because they are denied urban *hukou* status. Our results, therefore, are confined to that population group. For brevity, we often refer to urban wages when what is meant is the wages for registered urban residents. Analysing urban residents as a sub-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. Urban residents are likely to have been differentially affected by the loosening of controls over rural–urban migration in 1988 when the government allowed farmers to conduct business in cities, as Linge and Forbes (1990) discuss. Subsequent, 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 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. It is hard to separate the two curves for 1995 and 2002, but curve for 1988 clearly dominates these curves, while these in turn dominate that for 2008. 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. 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 and 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

[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] 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.

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

In modelling 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 two conventional variables to capture human capital are identified as productive characteristics: education in years and years of experience, the latter being entered as a quadratic[4]. In addition, occupation has been employed as one of the explanatory variable in order to identify wage gaps between skilled professional and low skilled workers. Other worker characteristics – sex, Communist Party membership, non-Han Chinese ethnicity – are controlled for as non-productive characteristics as *prima facie* they do seem likely to directly affect productivity. It has been commonly hypothesised that the transition from a command economy to a market-oriented system 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.). This is to identify changes of inequality between state-ownership and other ownership sectors. This is particularly important since the late 1990s when the state monopoly was put in place and further reinforced under the 2002 leadership. In this paper we also identify wage inequality and the changing trend among Chinese industrial sectors. We focus on manufacture sector which has been observed an important contributor to China's exportation and map out the details of wage gaps cross quantiles and the changes over time in relation to other key industrial factors. . The means of our explanatory variables are given in Table 2, and our discussion of the trends is presented in 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:

$$Q_\theta(w_{it} \vdots X_{it}) = X_{it}'\beta_t(\theta) \tag{1}$$

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.[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

4 Potential experience is measured as age in years minus (years of schooling plus six).
5 The distance between any two quantile points is 0.001.

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 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 favourable 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 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 α(.) is some summary statistics for wages – such as the gini coefficient – then we can decompose the changes in α as below:

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

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 $f^*(w(1); X(0))$,

[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)

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

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

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

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

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 analyse 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).

3. Results from Quantile Regressions

Figures 2 to 26 present the coefficients from quantile regressions for wages in 1988, 1995, 2002 and 2008.

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 confirms the overall rise in the return to education in urban China from 1988 up to 2002 that has been previously reported (Appleton, et al. 2005; Zhang, et al. 2005). The plotted line for 2002 dominates that for all previous years. 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). However, from 2002 to 2008, the reverse trend can be observed, with a fall in returns to education. Looking across the quantiles, in the first two surveys, the returns to education were higher at the lower end of the distribution For example, Figure 2 shows the return to education at the bottom end of the wage distribution reach 4% in 1988 but is less than 2% at the top end. This pattern has been observed in previous quantile regression analyses of wages in urban China (Knight and Song, 2002; Bishop, Luo and Wang, 2005). By contrast, in 2002, the returns to education fairly uniform across the distribution, lying in the 5-6% range. The rise in the returns to education from 1988 to 2002 was therefore greatest at the upper end of the distribution. The partial reversal of the rise in returns to education from 2002 to 2008 is also largest at the top end. From the 75th percentile onwards, the returns fall at an increasing rate and at the very top are around the 2% observed in 1988.

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 (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, 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 towards 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 between 2002 to 2008. One explanation which cannot be tested with our data is some high paid jobs could be obtained via bribery or using personal connections; a phenomenon is more commonly noticed and reported by the media in the past decade. This would show up in our decompositions as an 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 or state-sectors for which education is not the best measure of human capital: other unobserved skills or talents may be more important.

Figure 3 plots the returns to the other potentially productive worker characteristic, experience[7]. Contrary to the trends with education, it has often been found that the returns to experience fall during transition – for example, this was observed during the East European transitions (Svenjar, 1999). This has been explained as a consequence of pre-reform administered wages over-rewarding seniority. However, in urban China, the trends in returns to experience are less clear. The returns spike upwards from 1988 to 1995, drop sharply between 1995 and 2002, before rising again from 2002 to 2008. The pattern of returns has also become flatter across the distribution. In 1988 and to a lesser extent the next two rounds, the returns to experience are greater 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

[7] Experience was entered as quadratic in the wage functions and exhibited the conventional inverse U-shaped pattern. Figure 4 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.

pay scales. In contrast, in 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.

Wage gaps between occupations

The occupations of workers in our analysis are identified as private business owners, white collar workers (including professional or technical workers, managers, department heads, clerks), blue collar workers (skilled and unskilled) and others not belonging to any of occupations listed previously. In our models, the white collar workers are made the reference group.

Figure 5 shows that the earning differential between private business owners and white collars was almost indiscernible for most of the wage distribution in 1988. However, at towards the upper end of the distribution (from around the 80th percentile), private owners are paid slightly more. Over time, for the rest of the distribution, private owners have fallen behind white collar workers. By 2008, private owners in the lowest percentiles are estimated to earn around 5% less than white collar workers. 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.

There was little difference between the earnings of white collar and blue collar workers in 1988: the wage gap was less than 1% except for the very lowest paid. However, subsequent years have seen the gap widen in favour of white collar workers (Figure 6 refers). By 2008, the gap was around 3-4%. Between 2002 and 2008, 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. 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.

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 8 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 and Reilly (2007) 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 than men[8].

The pattern of gender coefficients across the quantiles has also changed over time. In 1988 and 1995, it follows something of an "L-shape". For most of the distribution, the gap in those

[8] 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.

years was around 7-8% but it was higher for bottom fifth, particularly in 1995. The gap roughly doubles to around 15% between 1995 and 2002 for the centre of the distribution. The plot of the gender gap for 2002 shows a generally negative slope. By 2002, the gender gap has increased further, to about 25% for the conditional median wage. However, the plot now is positively sloped. This is consistent with a “glass ceiling” effect whereby women at the higher end of the distribution face particular discrimination, although if so, it is a gradual and wide-ranging pattern rather than something which just applies to the top quantiles. Comparing the starting plot for 1988 with that for 2002, we can see the rise in the gender gap tends to somewhat greater as we move up the distribution. This is partly because there was already more of a gender gap at the bottom of the distribution in 1988 and partly because the gap becomes more pronounced at higher quantiles in 2002.

Figure 9 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. 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 (Li et al., 2007). 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 10 plots the coefficients for being non-Han Chinese. Wage gaps by ethnicity are modest in 1988, being only one or two percentage points and vary little across the quantiles. However, the gaps for 2008 are larger and more varied. Wage gaps are only unfavourable to ethnic minorities in the bottom half of the distribution and can become large, exceeding 25% at the 25% percentile.

Wage gaps by 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 from 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. 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. There was also strong growth in employment in foreign owned or joint venture companies, and in the “other” category. Conversely, the share of employment in SOEs falls, 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.

Figures 11-14 show the "pure" wage gaps between the various ownership sectors and the default SOE sector. Over time, pay in the urban collective sector has tended to fall further behind that in SOEs. By contrast, pay in the emerging ownership sectors (private, foreign and other) has risen relative to that in SOEs. As well as shifts in pay differentials by ownership, there have been 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 private or foreign enterprises. This suggests that 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.

Wage gaps between industrial sectors

Industrial sectors are classified into 12 categories with manufacturing set as the reference group[9]. Figures 15-25 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. Manufacturing is set as the reference group because it was by far the biggest sector in terms of employment in 1988 employing 43% of workers, with the second largest, wholesale and retail trade, employing only 14%. By 2008, manufacturing had shrunk in relative terms, employing only 17% of workers, whereas trade has expanded to cover 21%. Typically manufacturing pays more than trade, given worker characteristics. Figure 18 shows that the gap was modest in 1988, being less than 5%. However, the gap has widened over time, especially among the bottom 30% of the distribution.

The third largest sector in 2008 in terms of employment is public utilities and real estate. If we compare the wage gap for 2008 with that for 1988, the story is somewhat similar to that for trade in that the gap widens to further favour manufacturing for much of the distribution. However, for the top third of the distribution, the gap narrows and at the highest quantile is close to zero.

When we look at wage differentials with other tertiary sectors, the general trend has been the erosion of the privileged position of manufacturing workers. Ceteris paribus, workers in the civil service, in finance, in education, in social welfare and in science were paid less relative to manufacturing workers in 1988. By 2008, this differential had been reversed. There is some tendency for the improvement in the relative pay of these sectors to be proportionally larger, the further up the distribution we look. This is most apparent when comparing government civil servants with manufacturing workers: The wage gap between these two sectors is the same in 1988 and 2008 among bottom 10%, but progressively widens as we move along the distribution - reaching more than 20% towards the end.

[9] 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.

With the remaining industries - primary industry, construction and transport and communications - there were no sizable wage differentials relative to manufacturing in 1988 but by 2008, gaps in favour of those industries had appeared.

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. 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 and Mata, 2005). As part of the former, we investigate 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 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 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 to 1995 and the last, 2002-2008; 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. 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.

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 upwards across the distribution with somewhat larger increases at the bottom. Consequently, this did not contribute 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, *ceteris paribus,* would have increased the Gini coefficient by 0.041. Rises in the returns to experience from 2002 to 2005 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 - which the returns to experience were higher for the lower quartiles - but then increase it from 2002-2008, which higher quartiles enjoyed the highest returns to experience.

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 large effects on overall wage inequality. The decomposition shows a small negative effect on the Gini in 1988-1995, 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 has not had an appreciable effect on the Gini coefficient.

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 on inequality to be rather modest. It is only in the middle interval, 1995 to 2002, that there is a discernible effect: implying an increase of 0.012 in the Gini coefficient. This would have led to an increase in equality but for the offsetting negative residual item in the decomposition for that period. Changes in wage differentials by ownership initially had little impact on the change in inequality, but did contribute to rising inequality from 2002 to 2008 - accounting for an estimated 18% of the overall rise.

The widening wage gap between blue and white collar workers also contributed to the rise in inequality. During the first interval, 1988 to 1995, 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 the in the last period, 2002-2008, the 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 increased thereafter. In 1995 to 2002, they increased the Gini by 0.011 *ceteris paribus;* in 2002-2008, the contribution rose further to 0.026, a full quarter of the overall increase in the inequality. Figure 24, 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 has an unequalising effect.

5. 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 to 2008 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 and experience 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 generalisation 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 unfavourable unobservables - the low quantiles. By 2002, this pattern has all but been eroded before showing signs of emerging again in 2008.

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. In the most recent period, 2002 to 2008, changes in the returns to education and experience have actually been equalising. However, ever other category of observed wage differential - by sex, occupation, ownership, industrial sector and province – has served to widened inequality.

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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 5% - 95%	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: $QSK^{(p)} = [(Q^{(1-p)}-Q^{(.5)})/(Q^{(.5)}-Q^{(p)})]-1$ for $p < 0.5$. The quantity $QSK^{(p)}$ is re-centred 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

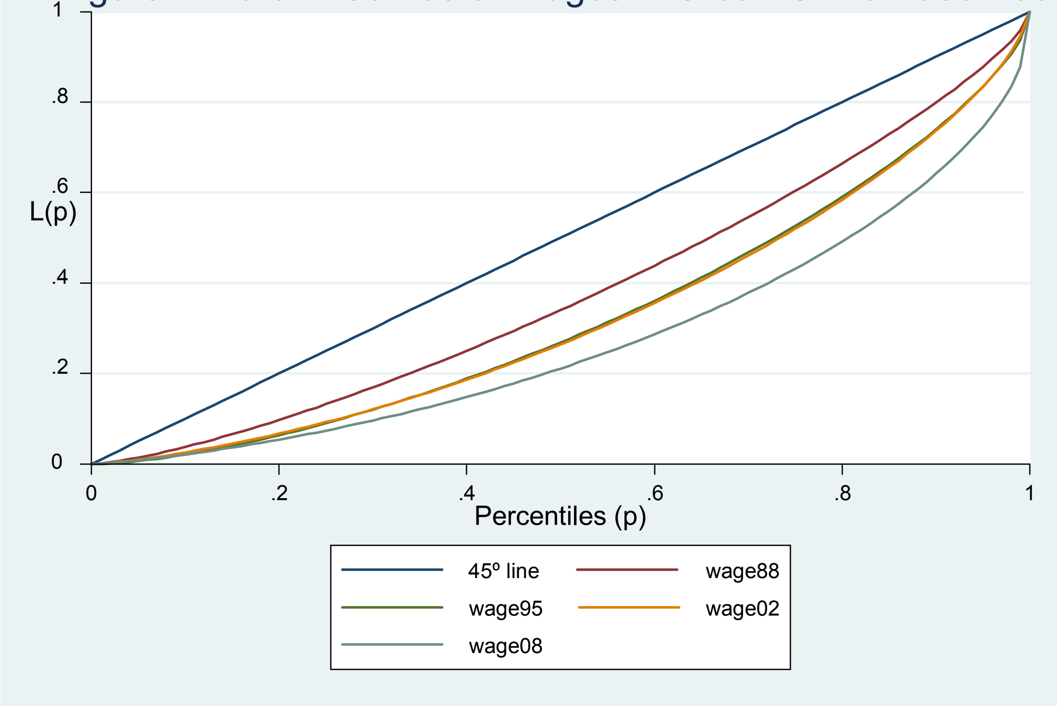
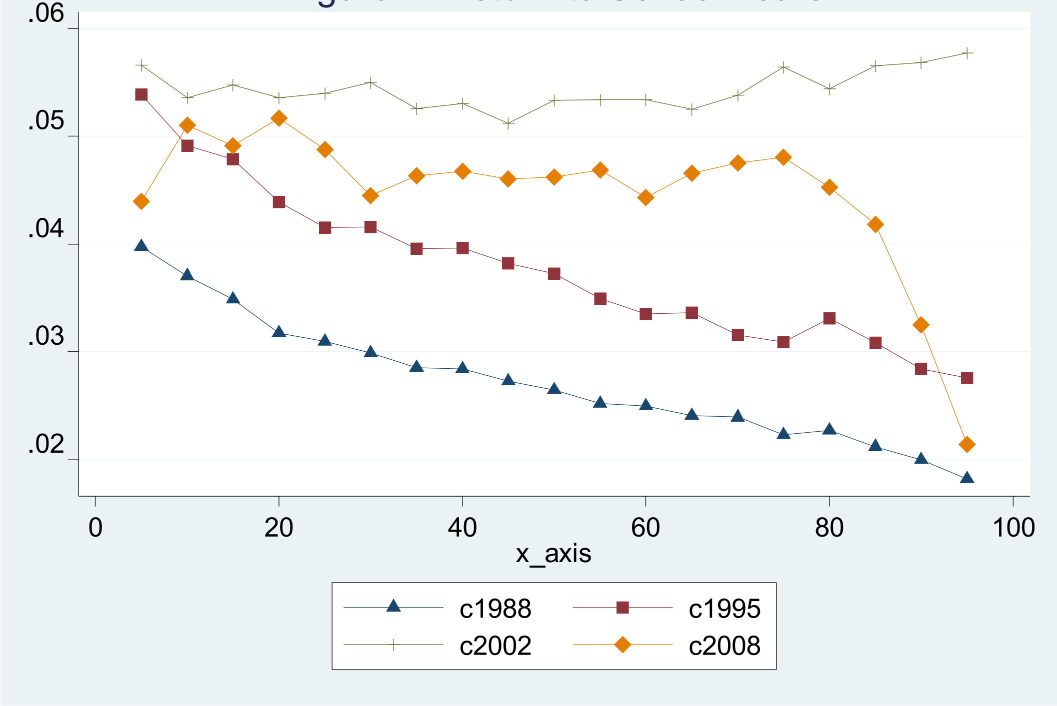


Figure 2. Return to School Years



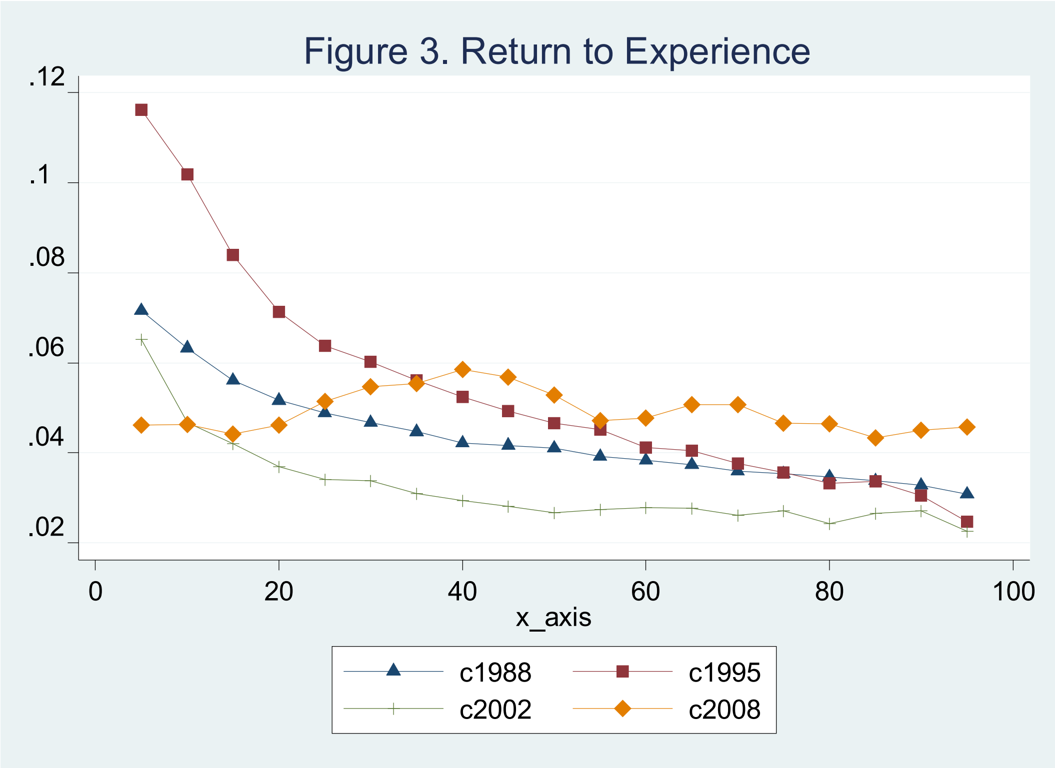


Figure 3. Return to Experience
.12
.1
.08
.06
.04
.02
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

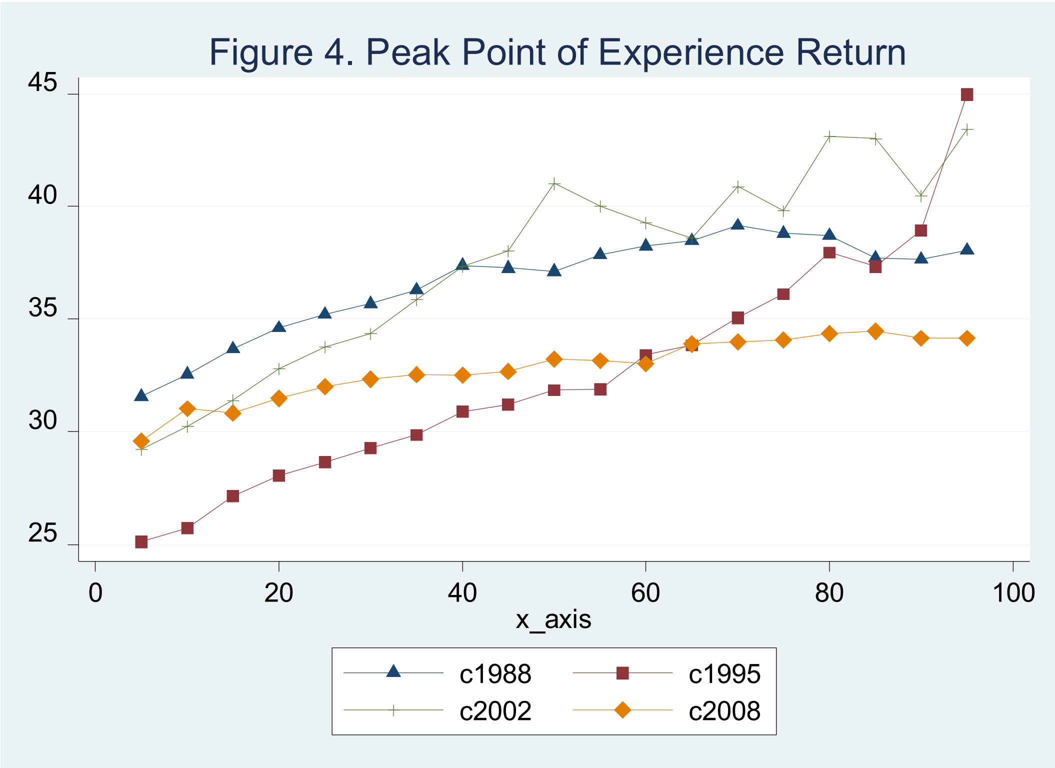


Figure 4. Peak Point of Experience Return
45
40
35
30
25
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

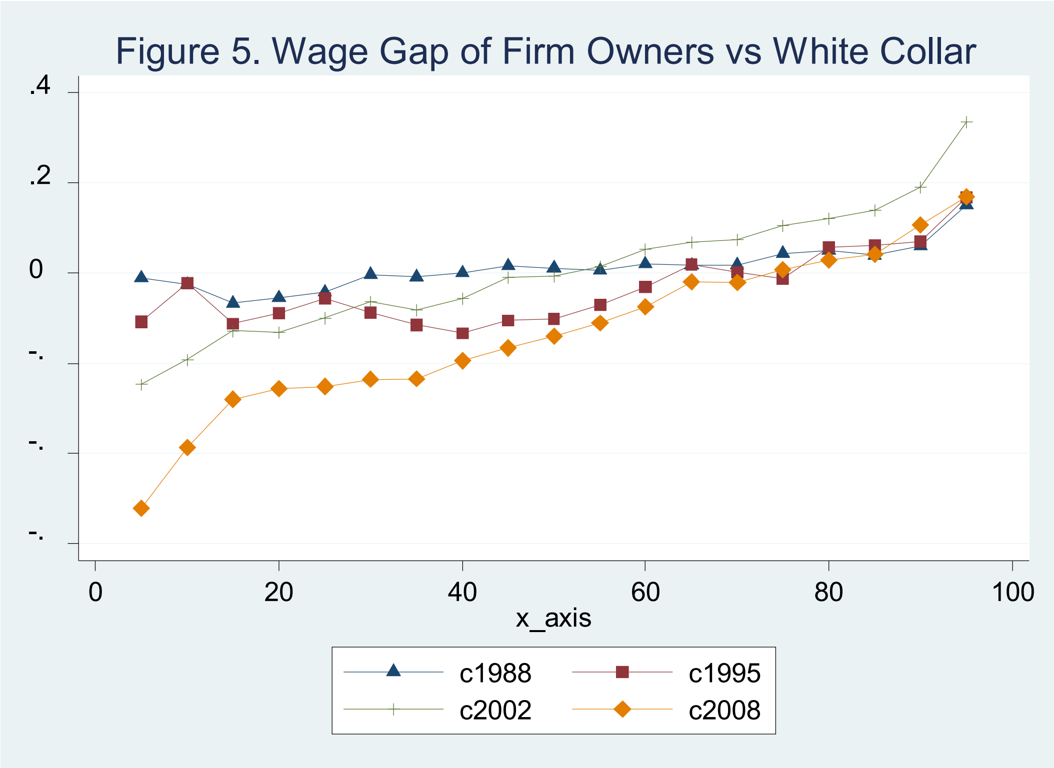


Figure 5. Wage Gap of Firm Owners vs White Collar
.4
.2
0
-.
-.
-.
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

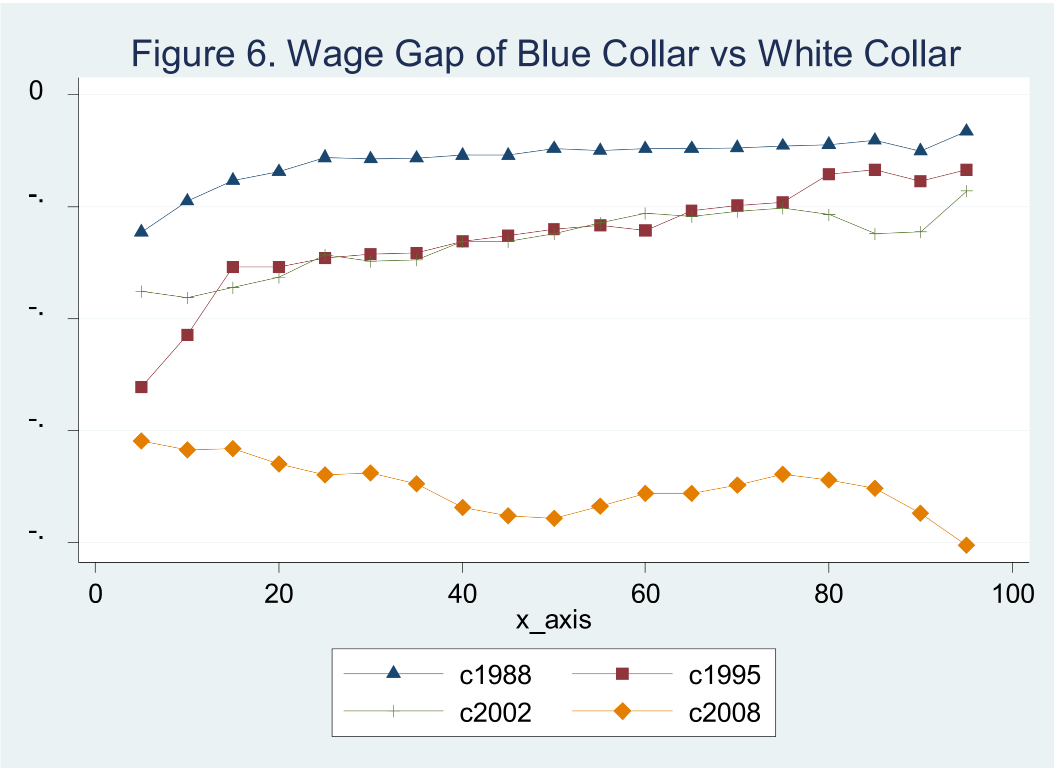


Figure 6. Wage Gap of Blue Collar vs White Collar
0
-.
-.
-.
-.
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

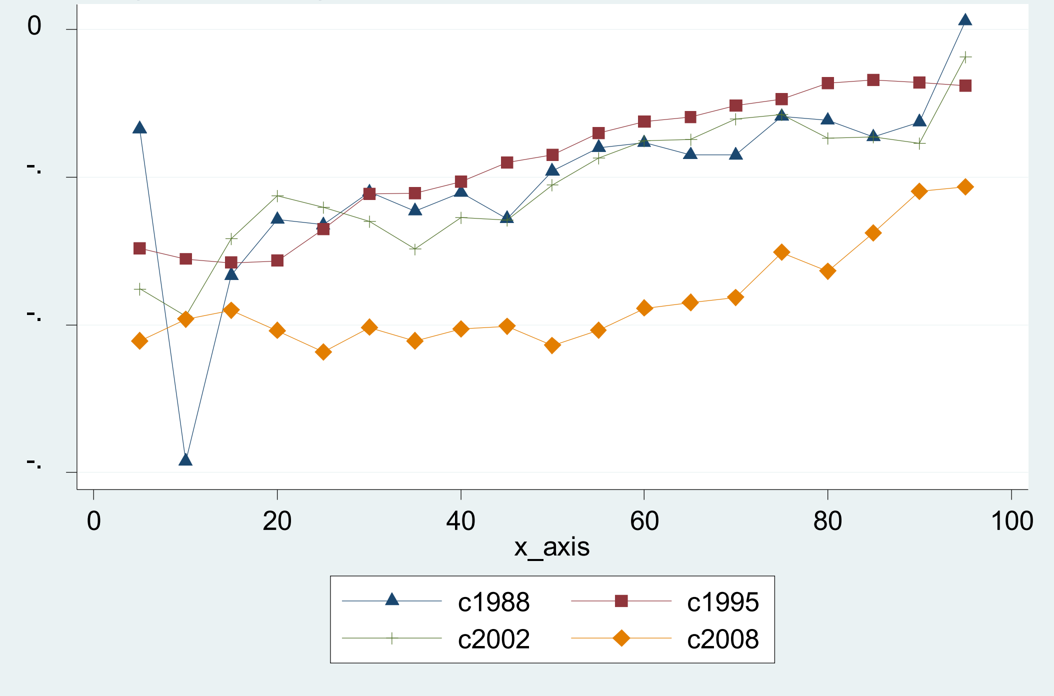


Figure 7. Wage Gap of Other Workers vs White Collar

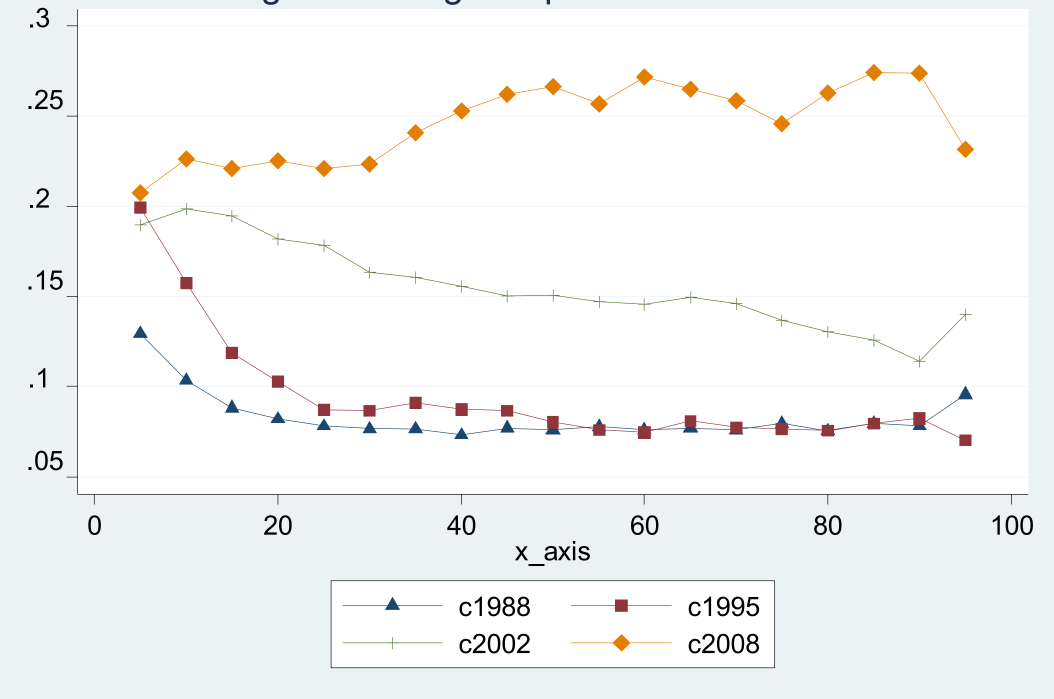


Figure 8. Wage Gap of Male vs Female

Figure 9. Wage Premium to Communist Party Members 1988-2002

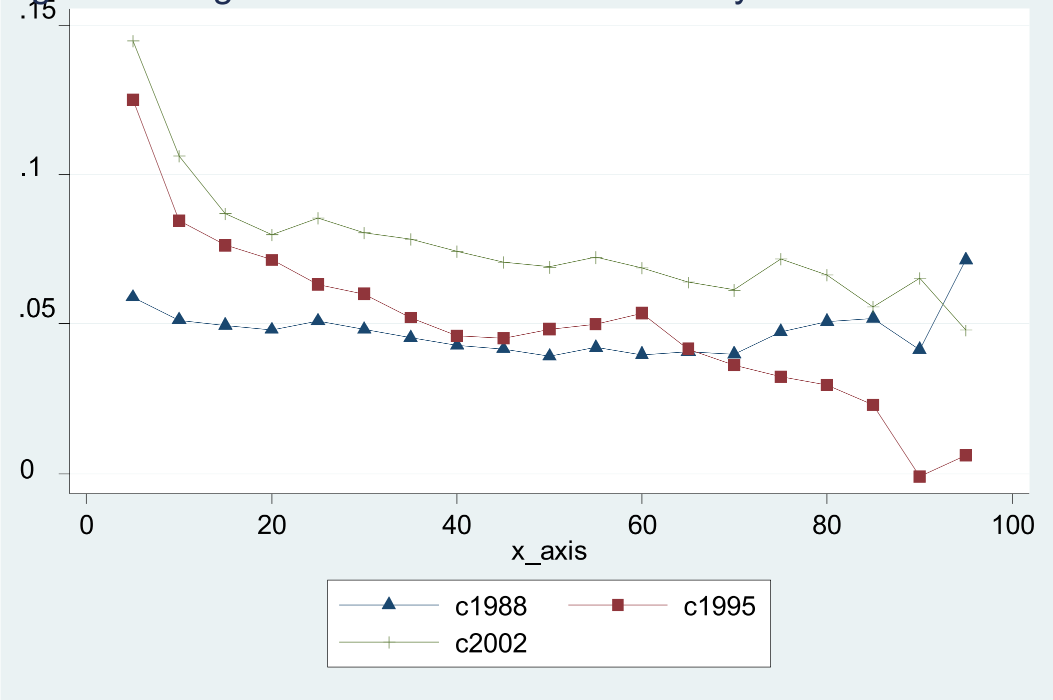
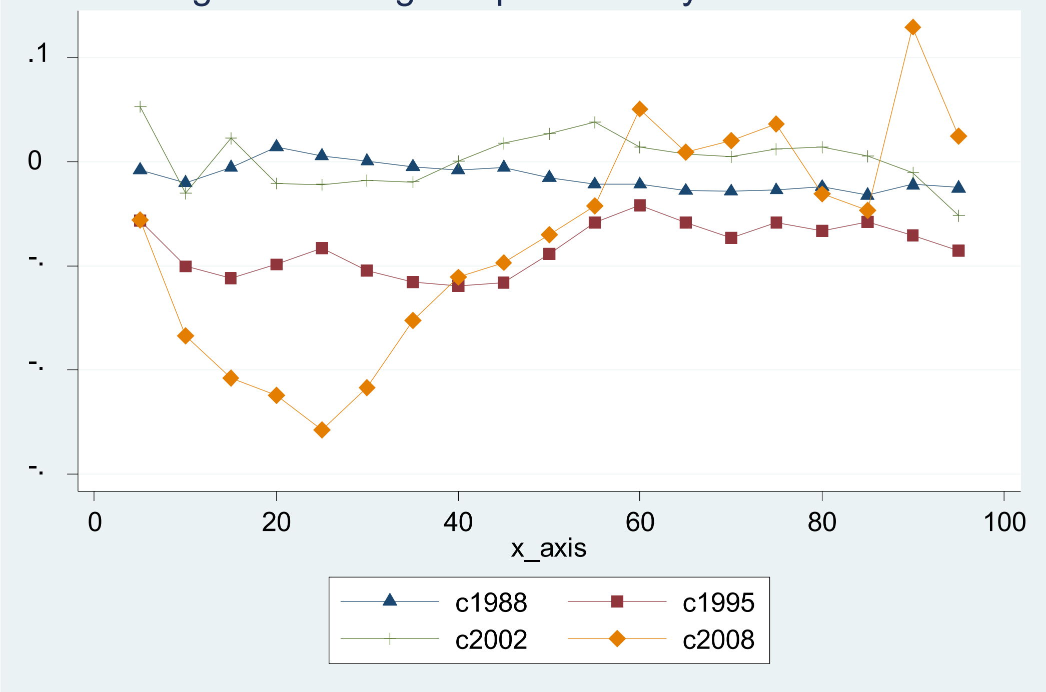


Figure 10. Wage Gap of Minority vs Han Chinese



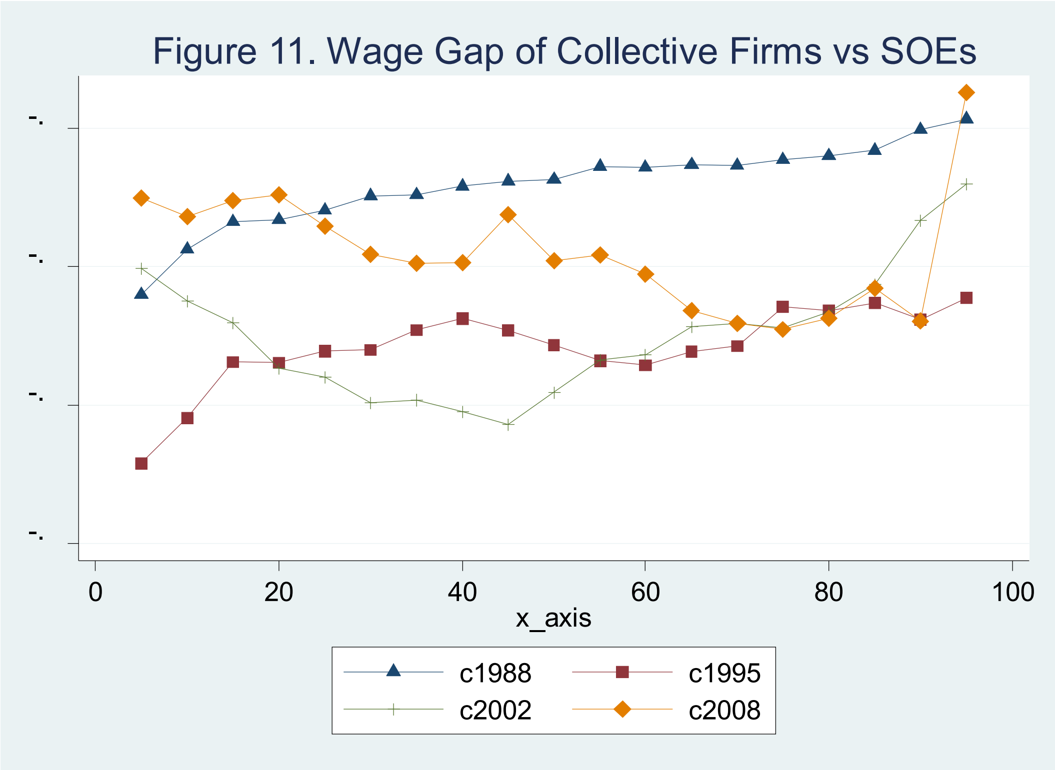


Figure 11. Wage Gap of Collective Firms vs SOEs
-.
-.
-.
-.
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008


Figure 12. Wage Gap of Private Firms vs SOEs
.5
0
-.
-1
-1.5
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

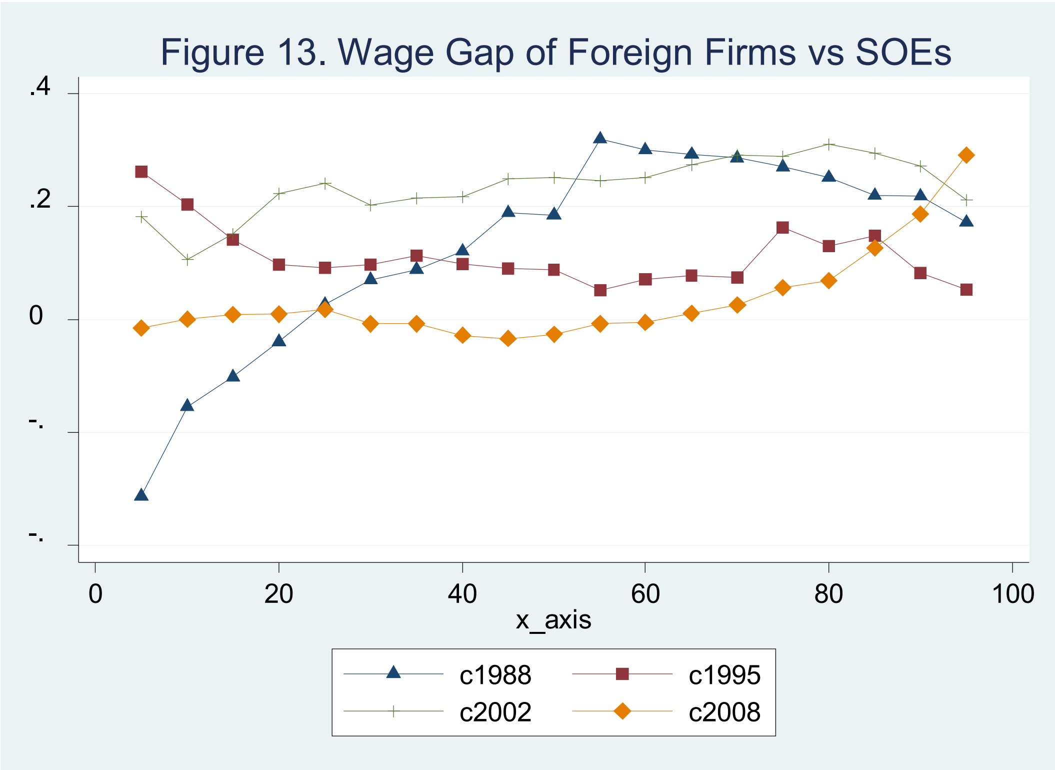


Figure 13. Wage Gap of Foreign Firms vs SOEs
.4
.2
0
-.
-.
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

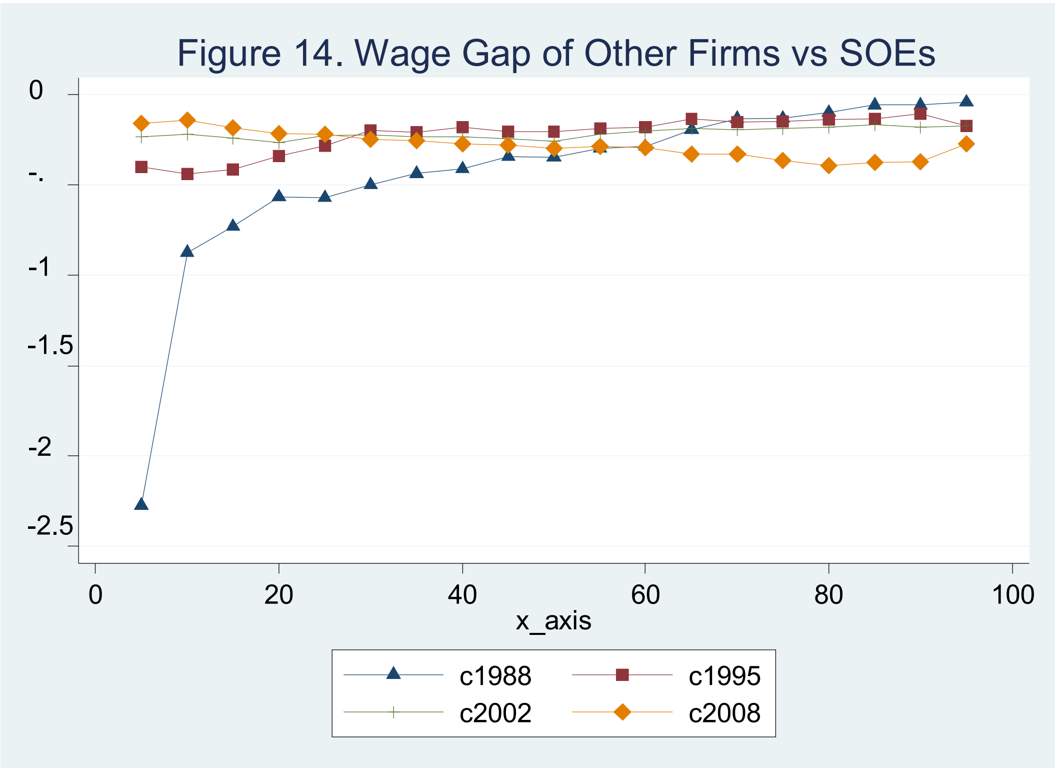


Figure 14. Wage Gap of Other Firms vs SOEs
0
-.
-1
-1.5
-2
-2.5
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

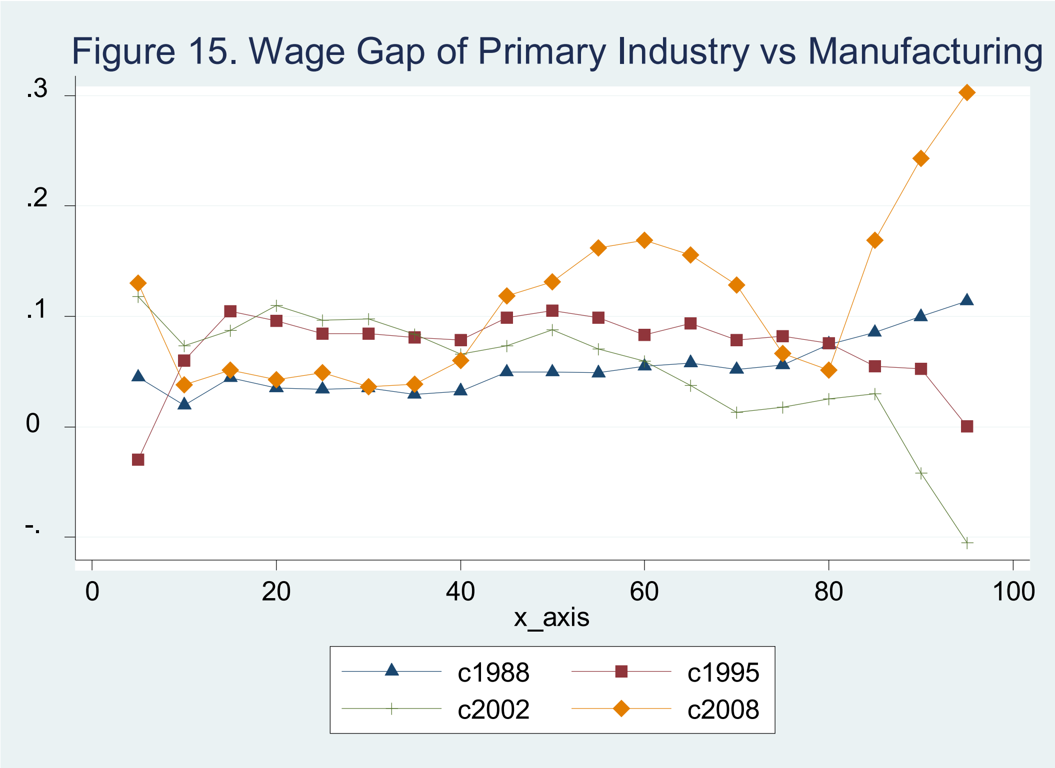


Figure 15. Wage Gap of Primary Industry vs Manufacturing
.3
.2
.1
0
-.
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

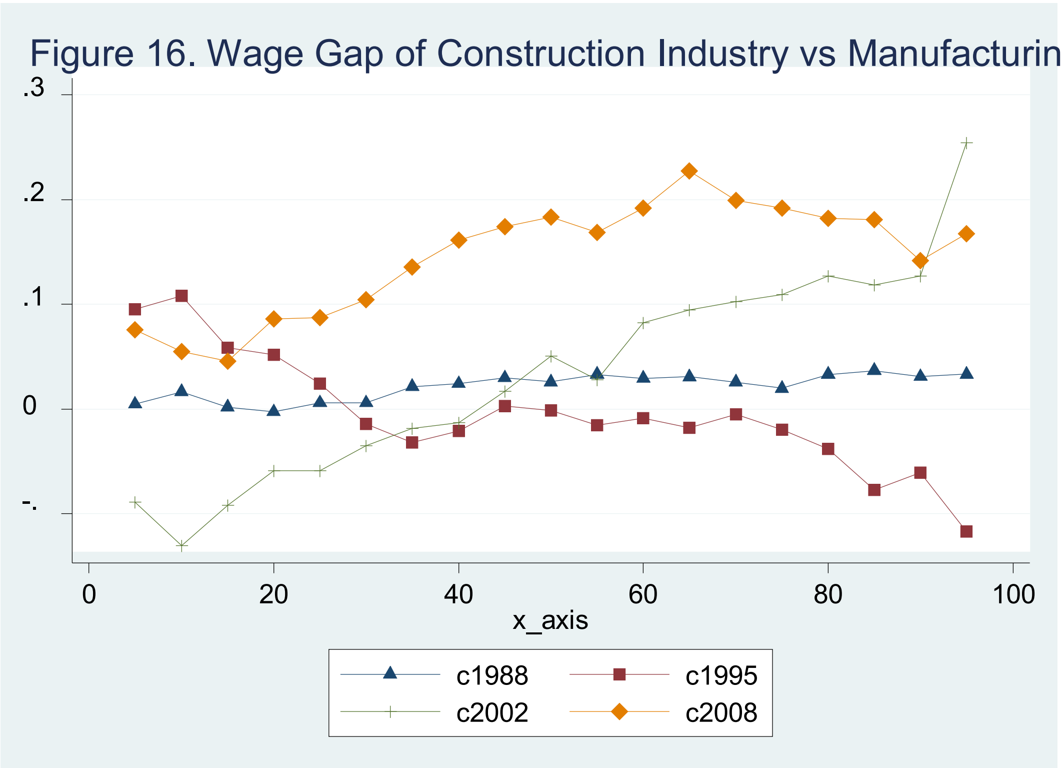


Figure 16. Wage Gap of Construction Industry vs Manufacturing
.3
.2
.1
0
-.
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

Figure 17. Wage Gap of Transportation & Communication vs Manufacturing

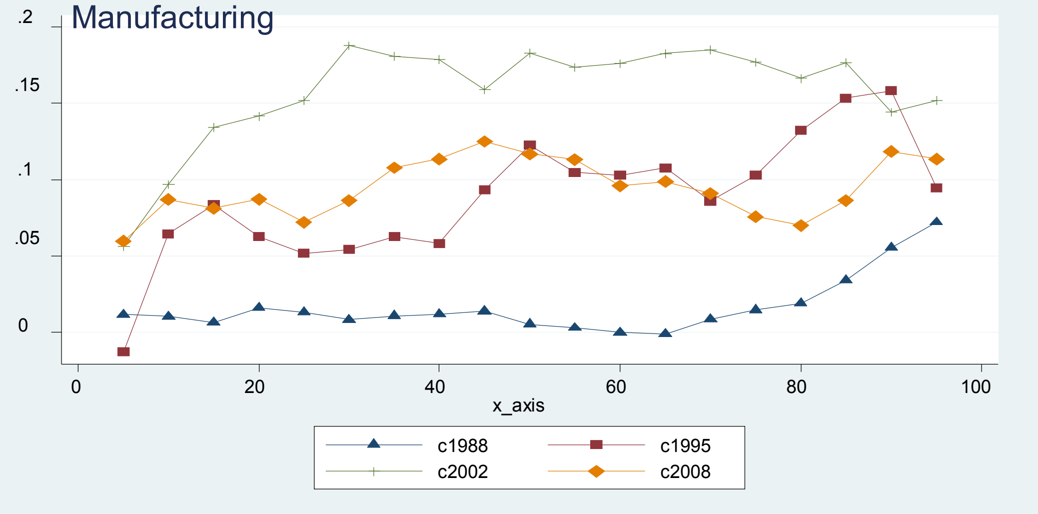
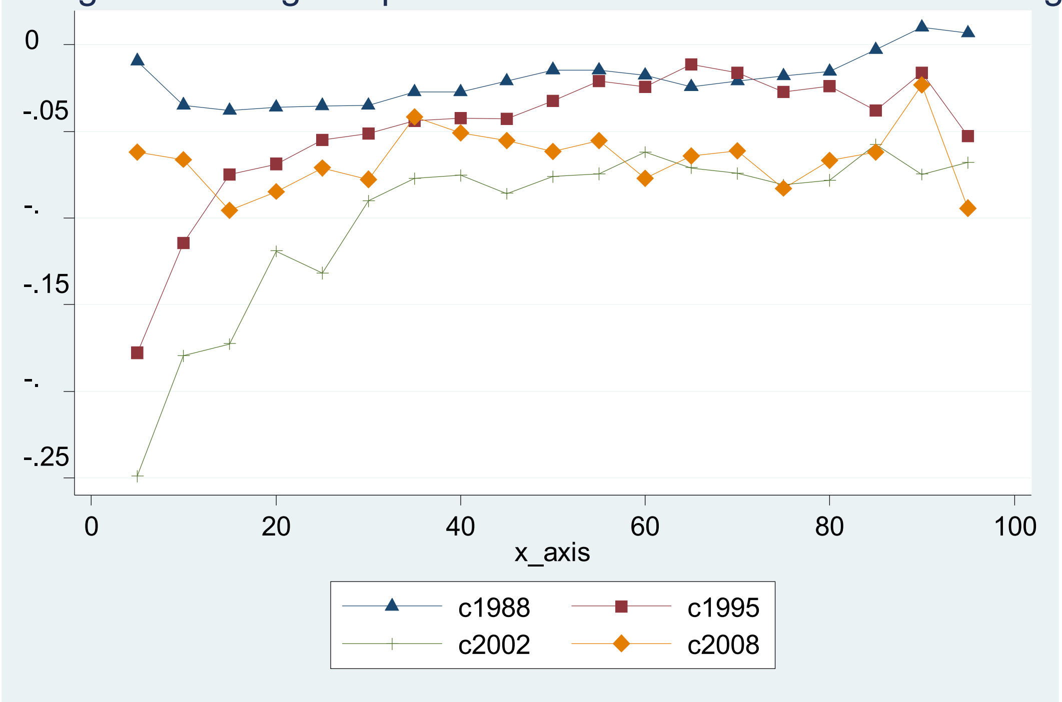


Figure 18. Wage Gap of Wholesale & Retail vs Manufacturing



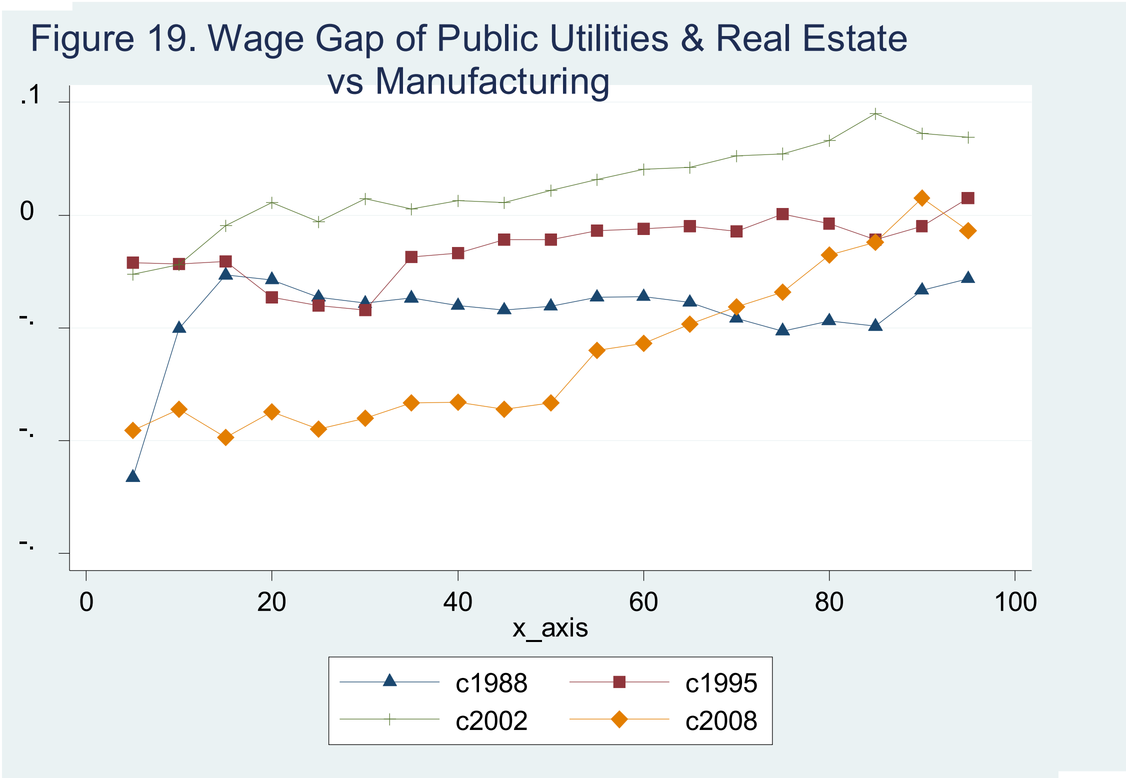


Figure 19. Wage Gap of Public Utilities & Real Estate vs Manufacturing
.1
0
-.
-.
-.
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

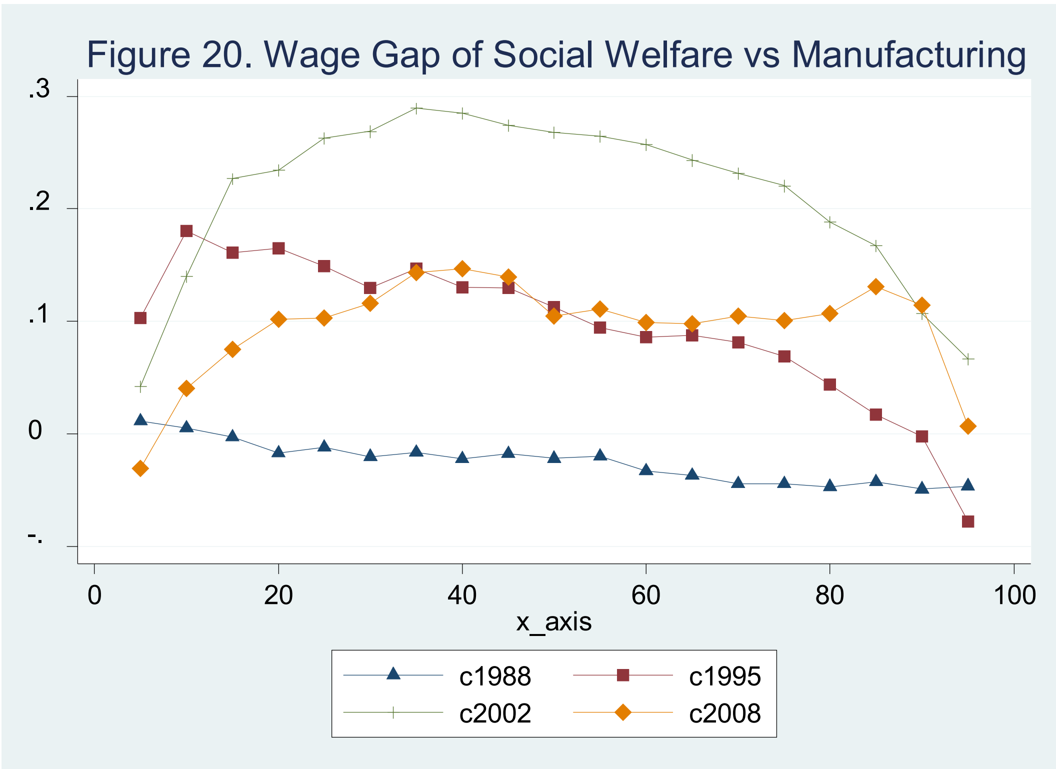


Figure 20. Wage Gap of Social Welfare vs Manufacturing
.3
.2
.1
0
-.
0
20
40
60
80
100
x_axis
c1988
c1995
c2002
c2008

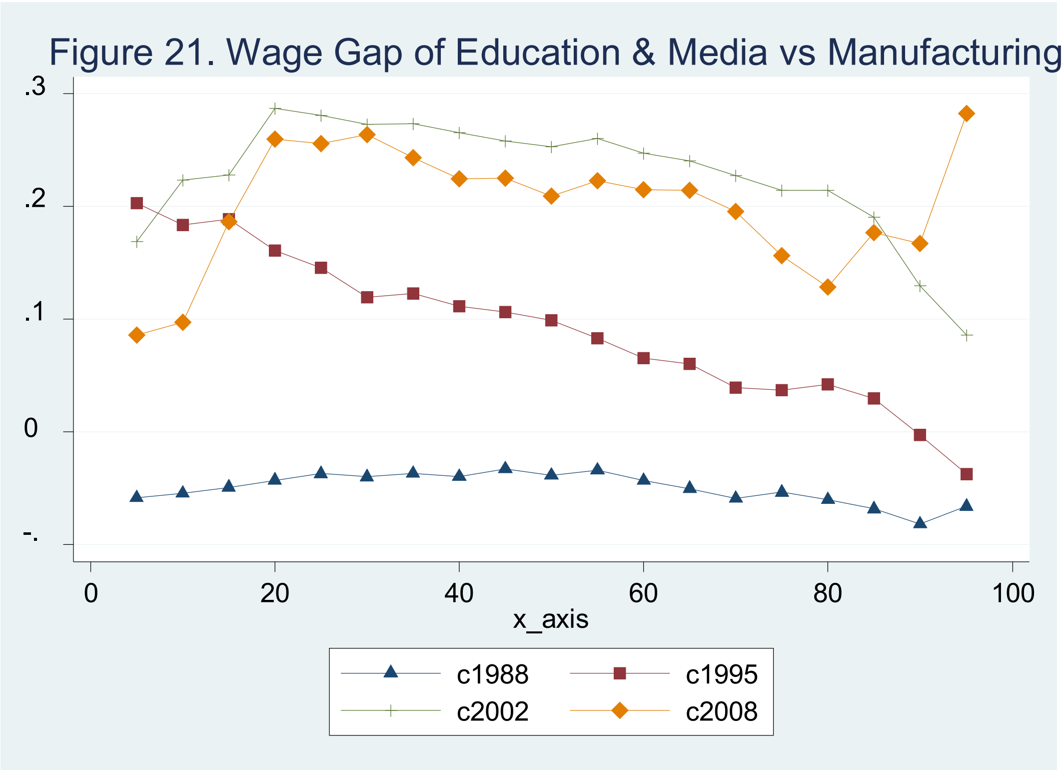


Figure 21. Wage Gap of Education & Media vs Manufacturing
.3
.2
.1
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0
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40
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80
100
x_axis
c1988
c1995
c2002
c2008

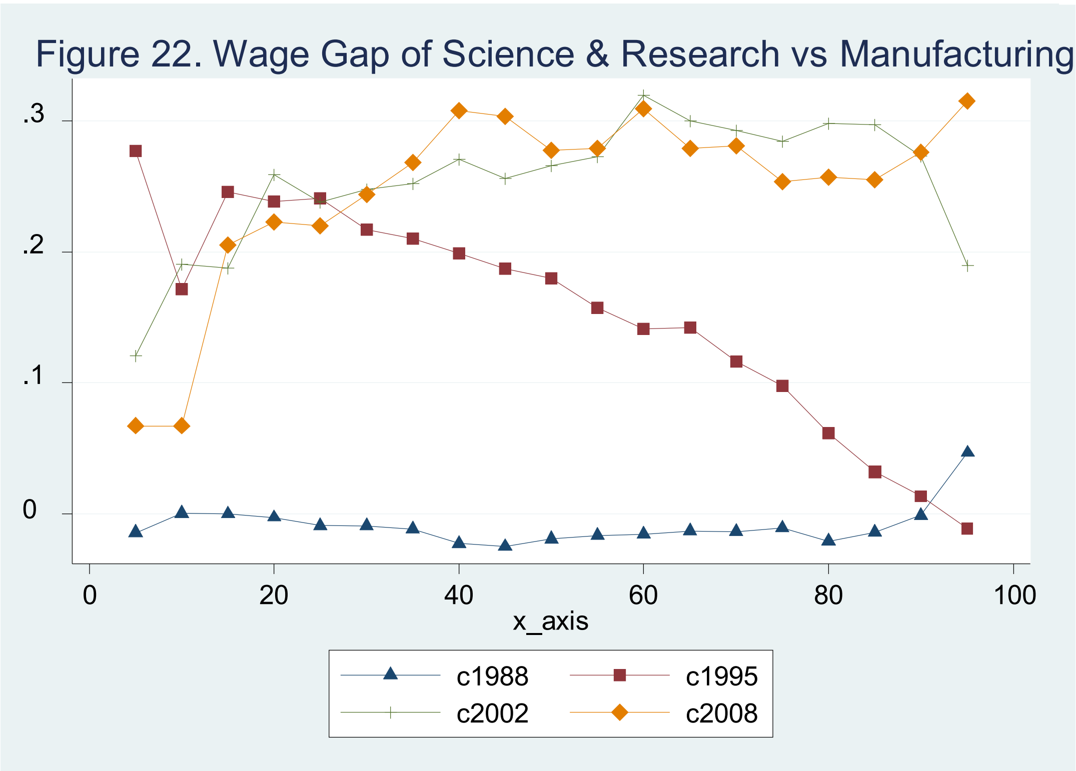
Figure 22. Wage Gap of Science & Research vs Manufacturing
.3
.2
.1
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0
20
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100
x_axis
c1988
c1995
c2002
c2008

Figure 23. Wage Gap of Financial Industry vs Manufacturing

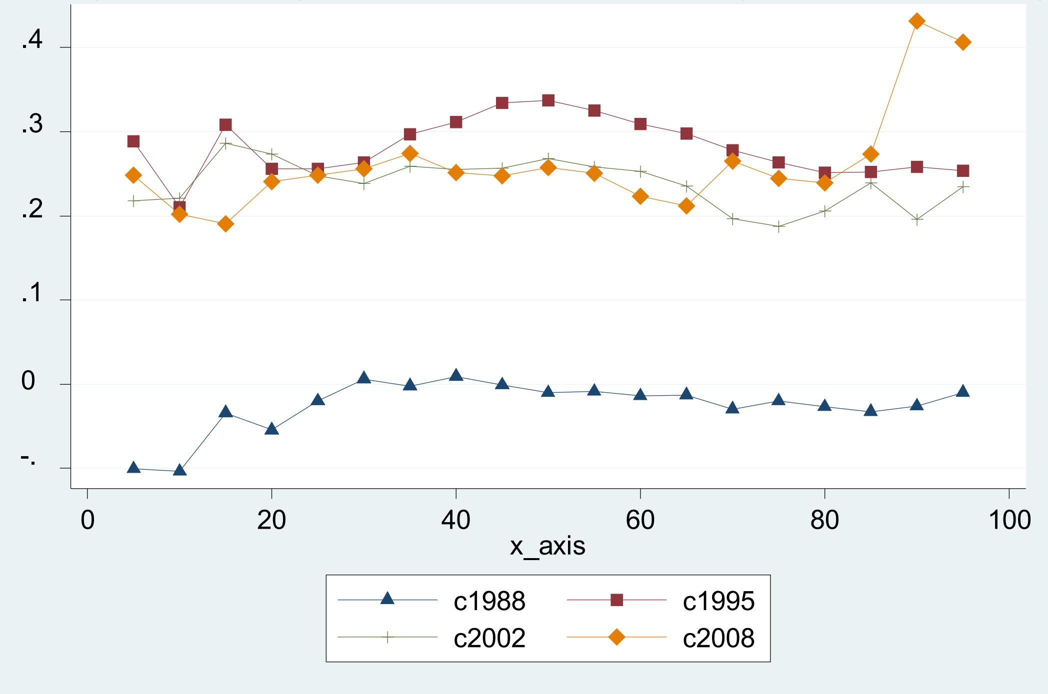

Figure 24. Wage Gap of Civil Servants vs Manufacturing

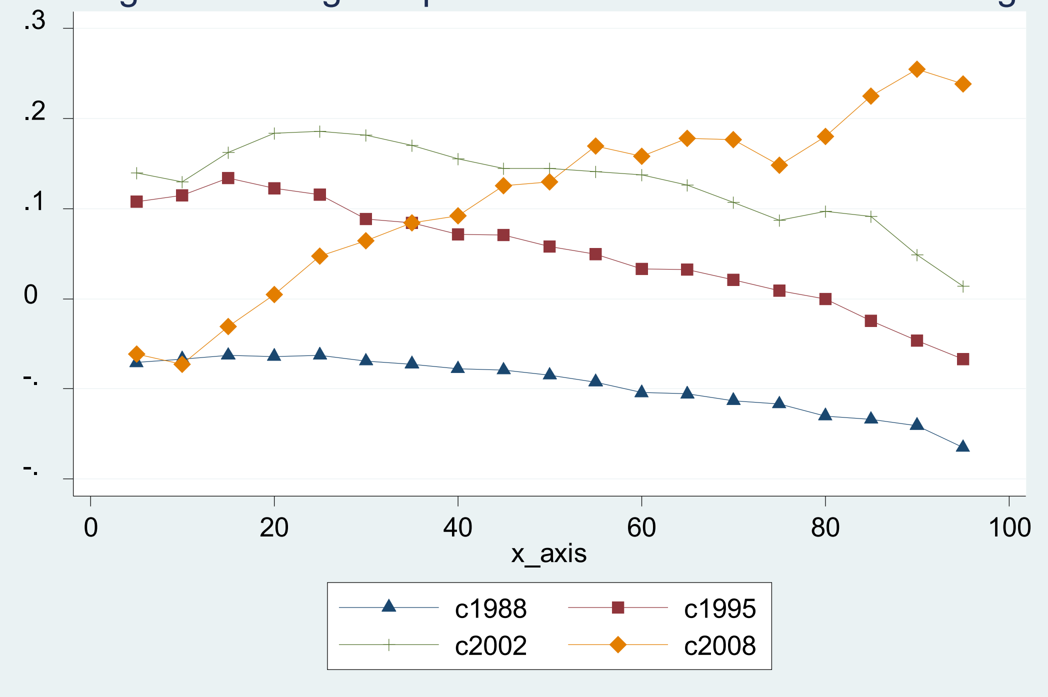

Figure 25. Wage Gap of Other Industries vs Manufacturing

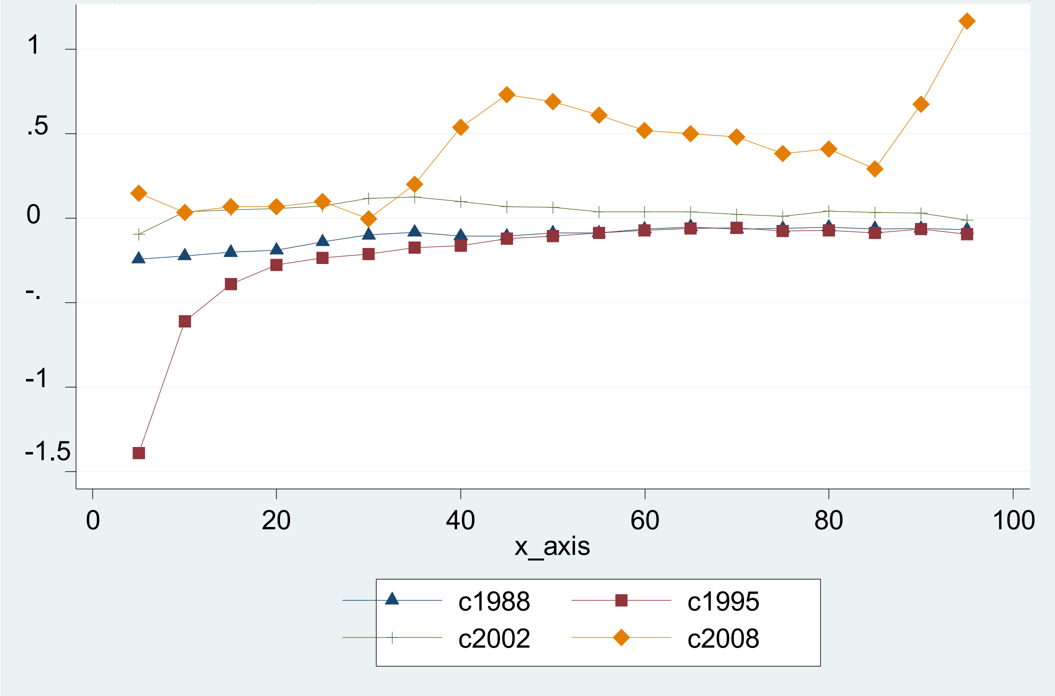

Figure 26. Constant Terms of Quantile Regressions

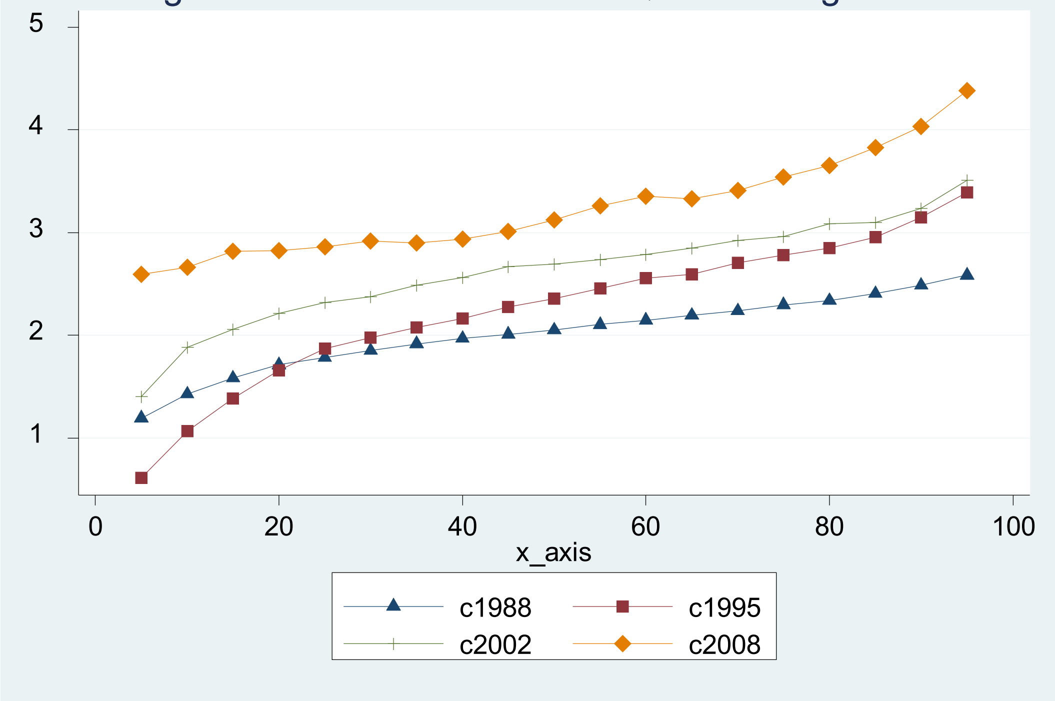

Table 2: Personal and job characteristics of the workers (%)

	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	10.51
Age in years	37.10	38.56	40.45	39.50
Experience in years	21.06	21.83	22.99	33.50
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.

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

	1988-1995	1995-2002	2002-2008
Change in Gini	0.108	0.003	0.102
Aggregate contributions to the change in Gini			
Covariates	**0.000** (-0.013, 0.021)	**0.013** (-0.005, 0.040)	**0.016** (-0.018, 0.003)
Coefficients	**0.121** (0.111, 0.135)	**0.002** (-0.009, 0.010)	**0.092** (0.075, 0.116)
Residual	**-0.013**	**-0.012**	**-0.006**
Contribution of covariates to change in Gini			
Sex	**-0.002** (-0.006, 0.000)	**-0.002** (-0.006, 0.003)	**-0.001** (-0.004, 0.003)
CP membership	**-0.003** (-0.004, -0.001)	**-0.002** (-0.003, 0.000)	**N.A.**
Minority	**0.000** (0.000, 0.001)	**0.000** (-0.001, 0.005)	**0.000** (0.000, 0.000)
Education	**-0.001** (-0.005, 0.003)	**-0.005** (-0.010, 0.005)	**-0.009** (-0.018, -0.003)
Experience	**-0.003** (-0.007, -0.004)	**-0.002** (-0.010, 0.006)	**0.007** (0.004, 0.010)
Occupation	**0.000** (-0.005, 0.005)	**0.001** (-0.007, 0.020)	**0.005** (-0.003, 0.013)
Ownership	**0.000** (-0.006, 0.003)	**0.012** (0.007, 0.018)	**0.000** (-0.017, 0.012)
Industrial sector	**0.001** (-0.008, 0.009)	**-0.001** (-0.008, 0.005)	**0.001** (-0.004, 0.010)
Provinces	**-0.003** (-0.012,0.010)	**0.002** (-0.013, 0.024)	**0.006** (-0.015, 0.020)
Contribution of coefficients to the change in Gini			
Sex	**-0.002** (-0.003, 0.002)	**-0.000** (-0.002, 0.001)	**0.017** (0.014, 0.019)
CP membership	**-0.004** (-0.006, -0.002)	**0.003** (0.002, 0.003)	**N.A.**
Minority	**0.001** (0.000, 0.005)	**-0.001** (-0.002, 0.000)	**0.000** (0.000, 0.001)
Education	**-0.002** (-0.004, 0.001)	**0.034** (-0.030, 0.040)	**-0.060** (-0.063, -0.054)
Experience	**-0.019** (-0.022, -0.016)	**0.041** (0.037, 0.044)	**-0.013** (0.009, 0.020)
Occupation	**0.012** (0.011, 0.015)	**-0.003** (-0.004, -0.002)	**0.009** (0.003, 0.012)
Ownership	**0.003** (0.000, 0.005)	**0.001** (-0.001, 0.005)	**0.018** (0.009, 0.033)
Industrial sector	**0.003** (-0.008, 0.011)	**0.011** (0.006, 0.026)	**0.026** (0.018, 0.045)
Provinces	**0.016** (0.009,0.025)	**-0.016** (-0.020, -0.011)	**0.029** (0.016,0.35)
Constants	**0.155** (0.147, 0.165)	**-0.054** (-0.060, -0.046)	**0.378** (0.300, 0.464)

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 sample 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) The maximum and minimum values of the 10 times replication is shown in the bracket.