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**DECOMPOSITION OF CHANGES IN
HONG KONG WAGE DISPERSION SINCE 1980s:
A DISTRIBUTIONAL APPROACH**

HUANG KAI WAI

MPHIL

LINGNAN UNIVERSITY

2009

DECOMPOSITION OF CHANGES IN
HONG KONG WAGE DISPERSION SINCE 1980s:
A DISTRIBUTIONAL APPROACH

by
HUANG Kai Wai

A thesis
submitted in partial fulfillment
of the requirements for the Degree of
Master of Philosophy in Social Sciences
(Economics)

Lingnan University

2009

ABSTRACT

Decomposition of Changes in Hong Kong Wage Dispersion since 1980s: A Distributional Approach

by

HUANG Kai Wai

Master of Philosophy

Wage dispersion is one of the social and economic issues arousing public concern in Hong Kong. There are many studies exploring the possible causes and changes in wage dispersion. They often focus on the study of summary measures such as Gini and Theil indexes, or adopt OLS-based regression approach. In foreign studies on wage dispersion, Oaxaca-Blinder decomposition, originated from Oaxaca (1974) and Blinder (1973), is a common method of decomposing changes or differences in mean wages between two groups into wage structure effect and composition effect, and then further decomposing the two effects into contributions of each control variable. Nevertheless, focusing on summary measures or decomposing mean wages can just give people an insight into the causes and changes in general wage dispersion but not the entire wage distribution. As pointed out by Chi, Li and Yu (2007), the estimation of the entire wage distribution and decomposition of the distributional changes in wage dispersion has been attracting the attention of labour economists. This thesis adopts a distributional approach proposed by Firpo, Fortin and Lemieux (2007) to study the changes in wage dispersion of Hong Kong since 1980s. The FFL approach comprises a two-stage procedure. Firstly, changes in dispersion are divided into wage structure effect and composition effect without directly estimating a wage-setting model. This is done by doing a proper reweighting to obtain counterfactual wage vectors. Kernel density estimation is used for visualizing the wage distribution in different years and the counterfactuals; secondly, novel recentered influence function (RIF) regressions across quantiles are performed to further decompose the two effects into contributions of each control variable. The findings are outlined as follows: first, there was an increase in wage dispersion over the whole wage distribution from 1980s but a decrease from 2001 to 2006; second, the composition effect dominates the wage structure effect over years; third, changes in the distribution of characteristics and the returns to these characteristics are highly responsive to each other, suggesting that our labour market is highly responsive to structural changes; fourth, The common wage-determining factors may not be able to explain the earnings-profile of low wage earners well. In brief, the development of the economy since 1980s increased the wage dispersion over years. Nevertheless, the economic

downturn due to external shocks and internal unfavourable events and general skill-upgrading in labour-intensive industries decreased the wage dispersion since 2000s.

Keywords: wage dispersion, Oaxaca-Blinder decomposition, FFL approach, kernel density estimation, RIF regressions.

DECLARATION

I declare that this is an original work based primarily on my own research, and I warrant that all citations of previous research, published or unpublished, have been duly acknowledged.

(HUANG Kai Wai)
July 5, 2009

CERTIFICATE OF APPROVAL OF THESIS

DECOMPOSITION OF CHANGES IN
HONG KONG WAGE DISPERSION SINCE 1980s:
A DISTRIBUTIONAL APPROACH

by
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Acknowledgements

I have been in Lingnan for five years with three undergraduate years and two MPhil years. Everything here is familiar to me. However, being a research postgraduate is very different from being an undergraduate. There is a wording mentioned by Prof Peter Baehr in our postgraduate seminar, which I would never forget: doing research is very lonely. Within these two years, I have learnt what it means and I encountered much time of frustration and sadness. Luckily, my time of MPhil study in Lingnan is not completely filled with loneliness. I had much joy from activities other than doing research. I paid much effort in being a good tutor and I developed friendship with my students; I had many chances to polish my Putonghua through the conversations with my mainland MPhilmates; and I enjoyed playing badminton with friends. My life here is filled with challenges and excitement. With this Acknowledgement, I would like to express my sincere thanks to my teachers, friends and family for their unconditional support and encouragement throughout my 2-year MPhil study.

First of all, I would like to express my immense gratitude to my chief supervisor, Prof Ho Lok-sang and my co-supervisor, Prof Wei Xiangdong. I have been being their students already since I was an undergraduate. I enjoyed their inspiring teaching. They have contributed much time and effort in guiding me patiently and won't be fed up with my questions. Prof Ho always has many valuable suggestions and comments on my research. I benefited a lot from the sharing of his distinguished knowledge in economics. Prof Wei was the supervisor of my undergraduate senior thesis. I am grateful for his inspiring guidance in these three years and I have learnt much in econometrics and labour economics from him.

My special thanks extend to other teachers in the Social Sciences programme. Prof Ma Yue is a warmhearted teacher and I learnt a lot from leading the tutorials of his course and the conversation with him; Prof Lin Ping always greets me with warm words of support and encouragement; Prof Peter Baehr is a very nice teacher and I learnt a lot about doing research from him; Dr Ran Jimmy is my teacher in econometrics and I would never forget his wonderful teaching; Dr Zhang Yifan helped me a lot by sharing with me papers in quantile regressions; and Dr Lei Kai Cheong is an inspiring teacher

for whom I admire early when I'm a year one undergraduate.

I also appreciate support from my friends in Lingnan. Thanks to Mr Xu Shu who has been teaching me the use of STATA and provided me lots of excellent research assistances; MPhilmates such as Ms LU Ruosi Sissi, Mr Xu Zhendong and Ms Wang Yiqun Lisa have enriched my life in Lingnan with much good humor and precious companionship. I would also like to express my deep gratitude to my loving family for their great tolerance and genuine support.

Last but not least, I would like to say thanks to her. The God seems to specially arrange our meeting. Everything is progressed just like a touching movie. I would never forget her soft encouragement and placid smile in my time of frustration.

Thanks to all who have given me kind support. I'm sure I have grown up with sweat and tears after these two years.

Chapter 1

Introduction

The growth and development of an economy often lead to an increase in the general level of wages. Through the dynamics of demand and supply in the labour market, workers with different characteristics and abilities provide different levels of marginal product and hence receive different level of wages. This gives rise to the issue of wage dispersion among workers, which has been one of the major concerns among labour economists.

Hong Kong is amongst those Asian economies experiencing rapid economic growth in the second half of the twentieth century, while at the same time having a continuous increase in wage levels. Chau (1984) mentioned that Hong Kong started its export-led industrialization process in the 1950s. Export-oriented light manufacturing such as textile and clothing became the engine of growth. The rate of increase in manufacturing employment was higher than that in total employment from 1950s onwards. A large pool of unemployed workers found jobs in the booming manufacturing sector, the construction sector and the sector of utilities and transportation. By the early 1960s, the economy reached a state of full employment¹. Almost half of the working population was working in the manufacturing sector by 1971. The wage rates of the working population rose in general within the twenty years from 1950s. Starting from early 1960s, the wage rates of workers with all skill levels have been increasing, with the rate of increase for unskilled and semi-skilled workers much higher than that for skilled workers. The export-oriented light

¹ Unemployment rate was only 1.7 percent of the working labour force, as noted by Chau (1984).

industries generally comprised small and medium sized enterprises, which implied that the market structure was close to the perfect competition setting. Besides, the labour-intensive production favored the employment of unskilled and semi-skilled workers. All these give rise to a faster rate of increase in wages for unskilled and semi-skilled workers and a reduction in unemployment, and in turn resulted in a decrease in wage dispersion. This seems to lend support to Kuznets' inverted-U hypothesis, which states that when an economy grows, income dispersion increases up to a certain level and then decreases².

Nevertheless, since 1980s, the dispersion of wages was increasing, as shown by the data of some common inequality measures such as Gini coefficient (Chau, 1984; Li, 2006; Lui, 2008). As noted by Cornia and Court (2001, p.13), "earnings inequality is influenced by changes in returns to education and experience and the overall supply and demand of different types of labour as well as by the institutions regulating the labour market". Other changes such as technological advances, changes in the degree of competition, institutions for wage-setting and government regulations can also be the reasons leading to rising wage dispersion (Danziger and Gottschalk, 2005). There are many studies giving various possible reasons of the increasing wage dispersion in Hong Kong since 1980s³. As the economic restructuring from manufacturing-orientation to service-orientation started in 1980s, some studies investigated the possible effects of economic restructuring on changes in wage dispersion. Lui (2008) suggested that the shift of employment from low inequality

² If household income is concerned, there was an increase in income dispersion from 1950s to 1960s since the top income owners were property owners, developers and industrialists and large windfall pecuniary benefits such as large amount of land rents during that time accounted for a large proportion in their income. From mid-1960s onwards, income dispersion decreased till early 1980s. See the Gini data in Table 1 of Chau (1984).

³ A more detailed discussion on the literature regarding Hong Kong wage dispersion since 1980s will be made in Chapter 2. A brief introduction is given here.

occupations such as plant and machine operators to high inequality occupations such as professionals underlies the total change in income dispersion from mid-1980s to mid-2000s by 40%; there are studies which explored the effect of immigration. Lam and Liu (2008) used a decomposition method based on the standard Mincerian wage equation and found evidence to support the view that immigration from the mainland played a role in HK growing wage dispersion in late 1990s; since trade is one of the key economic activities in Hong Kong, Ho, Wei and Wong (2005) conducted a time-series analysis and found that HK increased outward processing trade with the mainland has resulted in the polarization of income among workers with different educational levels in 1990s.

The above studies are mainly based on the analysis of summary measures or the OLS-regression approach⁴ except Lam and Liu (2008). Summary measures such as Gini coefficient and Theil index, which obey different commonly accepted criteria⁵, are popular among researchers as they are easy to be computed and provide people a quick overview on changes in wage dispersion. Nevertheless, as pointed out by some scholars such as Lemieux (2002) and Lui (2007), different summary measures may place different weights on different parts of the distribution, resulting in diverse messages about wage dispersion. They are nevertheless convenient when we want a simple comparison on inequality rankings; the OLS-regression approach is commonly used by economists to analyze economic relationships between dependent and independent variables. In labour economics, the Mincerian wage equation is commonly adopted for linking the relationship of wage with factors affecting wage levels such as education and working experience. Based on the set-up of Mincerian

⁴ A more detailed discussion on inequality summary measures and OLS-based Oaxaca-Blinder decomposition will be made in Chapter 3. A brief introduction is given here.

⁵ A brief account on the criteria will be given in section 3.1.1.

wage equation, a method called Oaxaca-Blinder decomposition is then performed to decompose the differences or changes in mean wages into the wage structure effect and the composition effect⁶ between two groups of workers under concern and further divide the two components into the contribution of each covariate (Blinder, 1973; Oaxaca, 1973; Borjas, 2000). This provides a more detailed picture on how changes of a factor can contribute to changes in mean wages through the two effects. Nonetheless, this decomposition method can only be applied on mean and is limited to addressing complex changes in wage distribution. It can only offer an anatomy of the summary measures. For studying changes in wage dispersion, an alternative approach considering the whole distribution instead of focusing on summary measures is more appropriate. The estimation of the entire wage distribution and decomposition of the distributional changes in wage dispersion has been attracting the attention of labour economists. This is known as distributional approach. There are two advantages in this approach. Firstly, it can better target the location of changes in wage dispersion. A change in a factor may either change the wage dispersion of the lower half or the upper half of the wage distribution. The distributional approach considering the whole distribution illuminates more information and can show a more complete picture unlike summary measures and mean decomposition which offers just an anatomy of the summary measures; secondly, the approach can provide a clearer indication of wage changes of extreme high wage earners or low wage earners. Estimation frameworks from parametric estimation to non-parametric estimation and quantile regressions can be categorized as methods within this approach. The Firpo-Fortin-Lemieux approach (FFL approach)

⁶ Wage structure effect is the effect on wages due to differences in returns to various labour market characteristics, while composition effect is the effect on wages due to differences in distribution of labour market characteristics of workers within the population (Chi, Li and Yu, 2007). More account will be made in Chapter 3.

is a method under the distributional approach, which involves reweighting and decomposition based on novel regression estimates called recentered influence function (RIF) regressions⁷. The advantages of the FFL approach are three-fold. Firstly, Like other methods in distributional approach, the FFL approach can allow researchers to “go beyond the mean” for studying wage dispersion; secondly, the reweighting procedure and RIF regressions can be easily and systematically done, unlike other kinds of distributional approaches which may require multiple resampling or other computationally intensive procedures; thirdly, we can further divide the two effects into the contribution of each covariate on any distributional statistics of interest such as across quantiles, on variance or on Gini, unlike other methods which can only divide effects of covariates into total wage structure effect or composition effect only. It is the third advantage which makes FFL approach superior to other methods under the distributional approach.

There are two motivations in this thesis. Firstly, as 1980s is the new era of increasing wage dispersion in Hong Kong since its miraculous growth and development began, the issue deserves attention both from the research and the policy point of view; secondly, as mentioned before, studies that focus on summary measures such as Gini coefficient or OLS-based regression approach such as Oaxaca-Blinder decomposition can only provide a general picture. Nevertheless, if we study the whole distribution, we can get a more comprehensive insight since wage dispersion may change very differently at different points of the distribution. Thus FFL approach, which is one of the methods in distributional approach, will be adopted for studying the issue. As far as I know, there are not many studies in Hong Kong which have adopted the

⁷ More detailed discussion on FFL approach and other methods of distributional approach will be made in Chapter 4.

distributional approach, not to mention the FFL approach, to study the issue of wage dispersion before⁸. This thesis is the first study to adopt the FFL approach for studying wage dispersion.

As mentioned before, through the consideration of the whole distribution of wages instead of focusing on summary measures or mean decomposition, we can know better about the changes in wage dispersion based on distributional changes rather than changes in aggregate measures. The findings in this thesis is outlined as follows: firstly, there was an increase in wage dispersion over the whole wage distribution from 1980s and but a decrease from 2001 to 2006; secondly, the composition effect dominates the wage structure effect over the years. This means changes in the distribution of labour market characteristics among the labour force are more important in shaping the dynamics of wage dispersion than changes in returns to the characteristics; thirdly, changes in the distribution of characteristics and the returns to these characteristics are highly responsive to each other, suggesting that our labour market is highly responsive to structural changes; fourthly, The common wage-determining factors may not be able to explain the earnings-profile of low wage earners well. In brief, the development of the economy since the 1980s increased the wage dispersion over the years. Nevertheless, the oversupply of highly educated workers and general skill-upgrading in labour-intensive industries decreased the wage dispersion since 2000s.

The remainder of this thesis is structured as follows: Chapter 2 is a literature review giving a general overview of wage dispersion in Hong Kong since 1980s; Chapter 3 introduces the traditional methods used to study wage dispersion and their

⁸ Lam and Liu (2008) is among the very small pool of studies which tried to focus the whole wage distribution. They estimated earnings function of the 10th, 50th and the 90th quantile and studied the effect of labour market factors and wage differentials between two different quantiles.

shortcomings; Chapter 4 is another literature review which focuses on distributional approach. The theoretical framework of FFL approach will be introduced in this chapter; Chapter 5 discusses the background, treatment and statistical portrait of the data; Chapter 6 introduces the empirical set-up of the methodology; Chapter 7 discusses the empirical results. Chapter 8 summarizes and concludes the discussion.

Chapter 2

Studies on Wage Dispersion in Hong Kong

2.1 Situation before 1980s

Since Hong Kong started its industrialization in 1950s, researchers have been exploring the issues of income⁹ dispersion in Hong Kong. Yet early studies were often hindered by poor sources of data. Studies on the size distribution of income by 1971 often showed a Gini coefficient of around 0.4 (Chow and Papanek, 1981). The estimates may be problematic due to three reasons. Firstly, data on employment were only obtainable from registered and recorded, relatively “large” enterprises with only twenty employees before 1980s. Thus the estimates were based on inadequate and unsatisfactory data; secondly, data did not allow the adjustment for household size, which might bias the estimates obtained; thirdly, some observations used for obtaining the estimates were “[derived] from different sources, using different definitions for different purposes, different sample designs and frames and, undoubtedly, with different degrees of errors and biases” (Chow and Papanek, 1981, p.471). Nevertheless, Chow and Papanek also suggested three reasons why comparisons of income distribution in Hong Kong should be more exact than that in other economies. Firstly, there should be less cases of under-reporting by the rich due to lower degree of fear from tax collector and political factors such as political attack; secondly, the definitions and methods adopted in different surveys were at least comparable due to the limitation of comparison to one economy. Studies on Hong Kong income distribution often focused on the changes of the situation in Hong

⁹ The word “income” may refer to “household income” or “labour income” in different studies on income dispersion.

Kong only and seldom made comparison with other economies; thirdly, since subsistence production was less in Hong Kong than elsewhere, valuation problems of producers' consumption could be avoided.

Most studies on wage dispersion before 1980s showed a decreasing wage dispersion. The wages of lower income groups have increased much faster than those of higher income groups, which was believed to be contributed by three factors as follows: i) the shift of workers from higher inequality occupations in primary sector to lower inequality occupations in manufacturing sector, ii) the higher rate of increase in low skilled workers' wages than that in high skilled workers' wages and iii) the rising female participation rate (Chau, 1984; Chow and Papanek, 1981). Many studies have focused on analyzing the effect of the first factor on Hong Kong wage dispersion before 1980s. Chau and Hsia (1978) studied how industrialization affects Hong Kong income distribution. Hong Kong has focused on producing a small number of highly labour-intensive products such as textiles and clothing, plastic and electronic products. Besides, entrepreneurs preferred the utilization of labour-intensive production techniques. "[The] choice of products and techniques, along with the wide adoption of subcontracting, has led to a proliferation of small firms" (Chau and Hsia, 1978, p.477). This creates a nearly perfectly competitive market and gives rise to a more even income distribution. Thus a tight labour market was possible to exist through the expansion in manufacturing sector, narrowing the intra-group as well as the inter-group wage differentials by industry. Furthermore, Chau and Hsia predicted that the within-group and between-group wage dispersion starting from 1980s would continue to be narrowing due to a lower rate of increase in the working population. The tighter immigration control and a trend of decrease in crude birth rate starting

from 1961 would give rise to a tighter labour market. Nevertheless, it turned out that wage dispersion in Hong Kong started to have a U-turn and worsened starting from late 1970s.

2.2 Situation since 1980s

The Hong Kong Census and Statistics Department has published a thematic report on Hong Kong household income distribution after the 2006 by-census was conducted. Data from 1996 by-census, 2001 census and 2006 by-census were used for analyzing the situation from 1996 to 2006. Although the focus of this report is on household income distribution instead of wage distribution, certain points in this report are worth noting. Four summary measures, namely the Gini coefficient, the mean logarithmic deviation, the Atkinson index and the Coefficient of Variation are used for comparing the income dispersion in different years. All measures, except the Coefficient of Variation, showed an increase in income dispersion from 1996 to 2006¹⁰. The report has suggested some possible reasons for the increase in income dispersion, e.g. decrease in sex ratio, population ageing and continuous increase in the population human capital level, but there is no empirical analyses and support for the reasons suggested.

Now let us consider the empirical studies that showed an increasing wage dispersion since 1980s (Chau, 1984; Li, 2006; Lui, 1997; Lui, 2008). Different factors that may contribute to changes in income dispersion were explored. Like many studies on wage dispersion before 1980s, the effect of economic restructuring has been widely

¹⁰ Here manifests a deficiency of summary measures for studying wage dispersion. More account will be made in Chapter 3.

explored, since sectoral shifts in employment derived from economic restructuring is believed to be a significant cause of increasing wage dispersion (Lui, 1997). Suen (1995) adopted the approach in Juhn, Murphy and Pierce (1993)¹¹ to decompose the variance of log earnings from 1976 to 1991. From 1976 to 1991, changes in within-industry composition and between-industry composition accounted for nearly 70 % of the increase in variance. This implies that the shift of employments within and across industries accounted for the increase in wage dispersion to a large extent. Nevertheless, from 1986 to 1991, changes in industrial composition accounted for only 28 % of the increase in variance. This shows that the effect of sectoral shift on wage dispersion decreased in late 1980s.

The issue of wage dispersion is not only the concern of economists but also that of other social scientists. Based on census data, Chiu and Lui (2004) discussed the process of social polarization that followed globalization in Hong Kong. They concluded that Hong Kong underwent a process of polarization in occupations and an increase in wage dispersion in the 1990s due to the transformation of an industrial economy into a service economy.

Lui (2008) is one of the most updated studies on Hong Kong wage dispersion. He adopted population census and by-census data from 1986-2006 for analysis. By considering the decile ratios, it is found that the wage dispersion of the higher income group has increased, while that of the lower income group has decreased. Following the approach of Juhn, Murphy and Pierce (1991) and Suen (1995), Lui also chose to decompose the variance of log earnings from 1986 to 2006. It is found

¹¹ Juhn, Murphy and Pierce (1993) is one of the pioneering works as an interim work between the traditional decomposition approach and the distributional approach. More discussion on this work will be made in Chapter 4.

that the change in industrial composition does matter in explaining changes in wage dispersion, but it actually helped to reduce the variance slightly. Apart from wage distribution by industry, Lui also considered wage distribution by occupation and by education. He found that the shift of employment from low inequality occupations such as plant and machine operators to high inequality occupations such as professionals explained the total change in income dispersion from mid-1980s to mid-2000s by 40%. He also found that the increase in the supply of post-secondary qualification and degree holders exceeded the increase in demand, leading to a decrease in the earnings premium for the better educated workers.

There are studies investigating the effect of trade on wage dispersion in Hong Kong. Fan and Cheung (2002) set up their hypotheses based on the Heckscher-Ohlin model and applied co-integration analysis to study how trade affected wage dispersion. They found that the increase in the wage differential between skilled and unskilled workers is associated with the increase in trade between Hong Kong and the mainland from the early 1980s to the late 1990s. This supports the Stolper-Samuelson theorem that trade with developing countries would lead to a lowering of relative real wages earned by unskilled workers in developed countries. Fan and Cheung (2004) further found that the increase in the proportion of degree holders in the labour force decreases the wage differentials in Hong Kong.

Ho, Wei and Wong (2005) studied the effect of increasing outward processing trade on wage dispersion by conducting a co-integration analysis on the quarterly time series data from 1991 to 2002. They found that the increasing outward processing trade between Hong Kong and the mainland increased the wages of higher educated

workers while decreased the wages of the lower educated workers, leading to a wage polarization and thus widening the wage gap. This is in line with the theory of how outward processing trade can affect wage dispersion¹².

There are also numerous studies on the effects of immigration on wage dispersion, including several studies by Lam and Liu. Their paper in 1998 takes account of the heterogeneity effect of immigration on wage dispersion through the decomposition of variance using census data in 1981 and 1991. It is found that a large proportion of the increase in measured inequality can be attributed to a change in population shares rather than an actual increase in wage dispersion. Another paper in 2002 showed that the wage divergence between natives and immigrants is a result of the divergence between the skill prices of education between them. The shift in skill demand caused by economic restructuring has a widening impact not only in the prices of the skills at different levels but also in the prices of skills from different sources. The latest study by Lam and Liu in 2008 extended previous works on immigration and used a decomposition method based on the standard Mincerian wage equation to study the situation of wage dispersion from 1996 to 2006. It is found that new immigrants have an earning disadvantage of about 62% relative to natives in 2006. Besides, the mean year of schooling of immigrants is lower than that of natives. These two factors account for the over-representation of immigrants in the 10th decile earnings group. Immigrant status can account for 5.9% of the total earnings gap between the 90th and the 10th decile groups. The findings support the common belief that immigration from the mainland has a significant role in the rising wage dispersion in Hong Kong.

¹² Increasing outward processing trade in terms of increasing trade of intermediate goods implies that the amount of labour intensive production processes becomes less in advanced countries. This lowers the demand for unskilled workers and thus increases the wage dispersion between skilled and unskilled workers (Ho, Wei and Wong, 2005).

Wage dispersion by gender, commonly termed as gender wage gap or gender wage differential, is also an area widely explored by labour economists. Many studies show that there is a decrease in the gender pay gap in Hong Kong since 1980s. Chan, Sung and Zhang (2001) studied how gender occupational segregation can affect the gender wage differential. It is found that the earnings-ratio between female and male increased significantly from 1981 to 1991. The results of the decomposition proposed by Brown, Moon and Zoloth (1980) show that the intra-occupation gender wage gap accounts for most of the total gap. Most of the intra-occupation gap is unexplained. The gender wage gap due to occupational segregation is small and females benefit more from the overall occupational segregation.

Fan and Lui (2003) tried to analyse the sources of decrease in gender pay gap theoretically and empirically using 1981 and 1991 census data. The empirical results support the theoretical model prediction that the decrease in gender pay gap is due to the change in female's comparative advantage and the gap is smaller in occupations which are less labour-intensive. Besides, females' productivity relative to males would increase during the economic restructuring from manufacturing-oriented to service-oriented, leading to the narrowing of the gender wage gap.

To sum up, there has been much literature in Hong Kong exploring different possible causes of the change in the wage dispersion. Among these studies except Lam and Liu (2008), the indications of any changes in wage dispersion are often based on the calculation of summary measures, or applying decomposition methods on inequality

measures¹³. Nevertheless, focusing on summary measures to study changes in the wage dispersion may lead to a misleading display of the situation. More account will be made in the following chapter.

¹³ Suen (1995), Lui (2008) and Lam and Liu (1998) adopted the method proposed by Juhn, Murphy and Pierce (1993) to decompose variance of log earnings, as briefly discussed earlier in this chapter.

Chapter 3

Traditional Approaches in Studying Wage Dispersion

3.1 Calculation of Summary Measures

3.1.1 General Background

For comparing the degree of wage dispersion across places or changes of wage dispersion over time, researchers construct quantitative measures. As noted by Hindriks and Myles (2006), the construction of inequality measures is based on the extraction of data from the income distribution and generation of a single number which can capture the inequality within that distribution. It is a consensus that a qualified inequality measure should satisfy some criteria. Lui (1997) suggested four criteria as follows:

1) *Income scale independence:*

The value of a measure should be the same regardless of the scale or unit of measurement of income. For instance, a measure should show the same degree of income dispersion no matter the income data is expressed in Renminbi or US dollars.

2) *Population size independence:*

The value of a measure should not be dependent on the size of the population under concern. For instance, when we combine a group of n persons with another group of $2n$ persons having the same degree of income dispersion as that of the former group, the value of the measure should have no change. Nevertheless,

Cowell (1995) said it is not clear that whether this criterion is desirable¹⁴.

3) *Pigou-Dalton condition*:

As stated by Hindriks and Myles (2006, p.416), it is a principle that “any transfer from a poor household to a rich one must increase inequality regardless of where the two households are located in the income distribution”. Any inequality measure which can conform to this principle is said to be sensitive to transfers.

4) *Decomposability*:

As stated by Cowell (1995, p.57), this criterion implies that there should be a close relationship between the income dispersion of the whole population distribution and that of its sub-groups. That means the total inequality can be expressed as a function of inequality within sub-groups and inequality between sub-groups.

Summary measures which can obey all or some of the above four principles are widely adopted for studying wage inequality¹⁵ (Coulter, 1989; Cowell, 1995; Lui, 1997). As pointed out by Lui (1997), they are often scalar inequality indices. Basic concepts of six commonly used summary measures will be discussed below.

3.1.2 Relative Mean Deviation

According to Cowell (1995, p.22), relative mean deviation “is defined as the average

¹⁴ For details, please refer to the discussion on building an inequality measure in Chapter 3 of Cowell (1995).

¹⁵ Not all measures obey all the four principles. Chapter 3 in Cowell (1995) summarizes the characteristics of different inequality measures on satisfying the four criteria and whether the values of a measure take on values ranging between 0 and 1.

absolute distance of everyone's income from the mean, expressed as a proportion of the mean". The measure is formulated as follows (Amiel and Cowell, 1999, p.139):

$$M = (n\mu)^{-1} \sum_{i=1}^n |\mu - y_i|$$

where n is the number of households/workers

y_i is the i th workers' income

The higher the value of M , the greater is the extent of wage dispersion. As noted by Hindriks and Myles, the advantage of using relative mean deviation is that it takes account of values within the entire distribution. Nevertheless, its linearity property implies that it is insensitive to income transfers from one person to another person if the persons involved both lie on the same side of the mean income¹⁶. It cannot obey the Pigou-Dalton condition.

3.1.3 Mean Logarithmic Deviation

Mean logarithmic deviation is a kind of generalized entropy measures of income dispersion¹⁷ (Hong Kong Census and Statistics Department, 2007b). It can be formulated as follows:

$$MLD = \frac{1}{n} \sum_{i=1}^n \log \frac{\bar{X}}{X_i}$$

¹⁶ Hindriks and Myles (2006) and Foster and Sen (1997) have provided good examples for explaining this inadequacy of relative mean deviation.

¹⁷ The other kind of entropy measure called Theil index will be discussed soon.

where n is the number of households/workers

$\bar{X}$ is the mean household/worker income

X_i is the household income of the i^{th} household/ worker's income of the i^{th} worker

The higher the value, the greater is the extent of wage dispersion. *MLD* is more sensitive to changes in the lower half of the distribution. The limitation of the *MLD* is that zero income is undefined. The thematic report transforms those household incomes with a value zero into \$0.1 for calculating the *MLD*, which certainly has bias.

3.1.4 Variance and Coefficient of Variation

Variance, a common measure of statistical dispersion, is also used by some researchers as a measure of wage dispersion. As noted by Conceicao and Ferreira (2000), if the share of income among individuals is the same, each of them must have the mean income and so the variance is zero; if the share is different from the mean this is captured by the variance. However, it is not a good measure of wage dispersion. Foster and Sen (1997) mentioned that the variance is dependent on the mean income level. A distribution may have a greater variation but a lower variance than another if the mean income level of the former distribution is much smaller than the other distribution. *CV*, the coefficient of variation, can better cope with this flaw by concentrating on relative variation. It is just the square root of the variance divided by the mean (Foster and Sen, 1997):

$$CV = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}}{\bar{x}}$$

The higher the value of CV , the greater is the extent of wage dispersion. As mentioned by Hindriks and Myles (2006), the procedure of square formation will give incomes further away from the mean more weight and so has certain sensitivity to transfer compared with the relative mean deviation. It is also better than the variance for studying wage dispersion as it is independent of the magnitude of the mean.

3.1.5 Atkinson Index

As mentioned by the Hong Kong Census and Statistics Department (2007b), the Atkinson index is different from other inequality measures in that researchers can specify the underlying social welfare function¹⁸ needed. Thus researchers can choose to put greater emphasis on any part of the distribution. The general form of the index is given as follows (Campano and Salvatore, 2006, p.82):

$$A_\varepsilon = 1 - \left(\frac{1}{\mu^{1-\varepsilon}} \int_0^\infty y^{1-\varepsilon} f(y) dy \right)^{\frac{1}{1-\varepsilon}}, \quad \varepsilon > 0 \text{ and } \varepsilon \neq 1$$

ε is the parameter which determines the weight being put on which part of the distribution. The higher the value of ε , the more weight is being put on the lower end of the income distribution. A_ε has a value between 0 and 1. The larger the value

¹⁸ The function for most measures is predetermined by the setting for weighting which affects sensitivity to changes at different level of the distribution.

of A_6 , the greater is the extent of wage dispersion.

3.1.6 Gini Coefficient

Gini Coefficient has the longest history and is the most often used inequality measure in social science disciplines (Coulter, 1989). It is “the ratio of the area between the Lorenz curve and the line of perfect equality to the total area under the line of perfect equality” (Ehrenberg & Smith, 2006, p.513). This implies that the Lorenz-based Gini Coefficient takes a range of values between 0 and 1. Firstly, the Lorenz curve is obtained through the plotting of a graph with cumulative percentages of household income as y-axis and the cumulative percentages of household number as x-axis. The extent of income inequality is manifested by the degree of concavity of the curve against the perfect equality line (Hong Kong Census and Statistics Department, 2007). The nearer the curve to the perfect equality line, the smaller is the degree of income inequality, and the smaller the value of Gini Coefficient. Mathematically speaking, Gini Coefficient can be expressed as follows (Burkhauser, Frick & Schwarze, 1997):

$$G = \left[\frac{1}{2n^2\mu} \right] \sum_{i=1}^n \sum_{j=1}^n |y_i - y_j|$$

where y_i and y_j are individual incomes

n is the number of individuals

The higher the G , the greater is the extent of wage dispersion. Foster and Sen (1997)

mentioned that arbitrary squaring procedure is not involved in the calculation of Gini coefficient compared with that of variance or coefficient of variation. Due to the property of being readily interpretable, the Gini Coefficient is widely included in many countries' demographic reports. In addition, because of the high degree of availability of this data, it is widely utilized in many studies on wage dispersion. Nevertheless, Gini is not decomposable. As illustrated by an example in Cowell (1995), Gini may show an increase in inequality in all sub-groups of the population but end up in a decrease in the overall inequality¹⁹.

3.1.7 Theil Index

The Theil index is another popular inequality measure among researchers. It is based on the direct derivation from the principle behind entropy in statistical thermodynamics and information engineering (Coulter, 1989). It can be decomposed additively, allowing the general income inequality pattern to be divided into differences between and within subgroups (Burkhauser, Frick & Schwarze, 1997). Citing the example provided by Coulter, the population under study can be partitioned into several age groups with an additively decomposable measure for determining general income inequality. The degree of contribution by within-group inequality and between-group inequality can also be determined. The mathematical formulation of the Theil index is as follows (Burkhauser, Frick & Schwarze, 1997):

$$I_1 = \frac{1}{n} \sum_i \frac{y_i}{\mu} \log \frac{y_i}{\mu}$$

¹⁹ There are many other deficiencies of Gini coefficient. A more detailed discussion can be found in Chapter 3 of Coulter (1989).

where y_i is the i th workers' income

n is the number of individuals

The higher the value of I_1 , the greater is the extent of wage dispersion. I_1 is possible to be decomposed as follows:

$$I_1 = \sum_{g=1}^G v_g I_{1g} + \sum_{g=1}^G v_g \log \left(\frac{v_g}{p_g} \right)$$

The first term captures inequality within each of the G population sub-group, while the second term captures that among those subgroups by $v_g \cdot v_g$, as noted by Coulter, is the total income share in subgroup g . p_g is the proportion of the total population within the group. Compared with relative mean deviation, the Theil index is less bottom-sensitive; compared with Gini, it also has the advantage that it is decomposable.

3.1.8 Inadequacies of Using Summary Measures

Although summary measures are commonly adopted in the study of wage dispersion, as noted by Lui (2007) and some other related literature, not all measures can meet the four criteria mentioned earlier. It is not a consensus among researchers that whether a measure chosen for studying wage dispersion should meet all the criteria. Gini coefficient, the widely adopted summary measure, can only obey the first three principles. This may not be critical, if the measures could really provide a convincing

and comprehensive picture on the changes in the wage dispersion. Nevertheless, this may not be the case. There are two main inadequacies of using summary measures in studying wage dispersion through the consideration of the whole distribution.

Different measures may implicitly put different weights on different parts of the wage distribution, resulting in misleading display of wage dispersion (Lemieux, 2002; Sen, 1997). For instance, the Gini coefficient emphasizes more on that part of the distribution where the density is greatest, and this is often, not always, the lowest part of the distribution (Bojer, 2003); the squaring procedure of coefficient of variation emphasizes more on extreme parts of the distribution regardless of the lower end or the upper end; the Theil index and the Atkinson index have a higher sensitivity to income dispersion at the upper levels and at the lower levels of the wage distribution respectively (Braun, 1988). Thus the Gini alone and other inequality measures cannot tell the full story. They must be supplemented by other measures to illuminate the full effects of changes in the wage dispersion on inequality (Bojer, 2003; Hong Kong et al, 2007b). For example, Burkhauser, Frick and Schwarze (1997) used Gini coefficient and Theil index data from the United States Panel Study of Income Dynamics and the German Socio-Economic Panel during 1984 to 1989 to compare the economic well-being of the United States and Germany. They find that income inequality in United States is greater than that in Germany regardless of which measure is considered; the thematic report discussed in Chapter 2 adopts four measures to study the household income distribution, but the coefficient of variation shows a decreasing trend of income inequality, which is opposite to the situation indicated by the other three measures. The report concluded that there is a trend of increasing income inequality because three out of four measures have such an

indication, but this conclusion is somehow arrived arbitrarily. It is difficult to give a definitive conclusion if the story shown by half of the measures contradicts that shown by the other half.

Furthermore, indexes such as Gini may summarize differences between two distributions with a single number, which is misleading²⁰. Deininger and Squire (1996, p.567) has pointed out this problem precisely:

... there is no unique mapping between changes in the index and the underlying income distribution; redistribution from the top to the middle class may be associated with the same change in the aggregate indicator as an increase in the share of income received by the bottom quintile at the expense of the middle class.

Many measures fail to indicate the region of the wage distribution in which most of the changes occur. This leads to little provision of information on different shapes of different distributions and so changes in wage dispersion actually (Dinardo, Fortin, and Lemieux, 1996). They are often more convenient for usage when we want a simple comparison on inequality rankings. More and more researchers try to consider the quantiles of the whole distribution instead of focusing on the use of summary measures. By studying changes in wages at different quantile levels, the changes in wage distribution can better be detected. For example, the thematic report on Hong Kong household income distribution mentioned earlier also considers

²⁰ The discussion in Chapter 3 on Figure 3.2 of Lui (1997) can illustrate this point precisely. In brief, the areas between the Lorenz curves and the line of perfect equality made by two income distributions can be the same, giving rise to the same value of Gini.

median monthly household incomes by decile groups and finds that the median monthly incomes for the first eight decile groups decrease while those for the ninth and the highest decile groups increase.

3.2 Decomposition Methods

3.2.1 General Background

Apart from calculating summary measures, decomposition methods based on regression techniques are also popular in studies of wage dispersion for quantifying the impact of different factors. A wage or income generating function must be obtained as the first step of many regression-based decomposition methods. The function is often based on the Mincerian wage equation proposed by Mincer (1974) as follows (Education and Manpower Bureau, 1999, p.8):

$$\ln Y = \alpha + \beta S + \gamma_1 E + \gamma_2 E^2 + f_n X + \varepsilon$$

where $\ln Y$ is the natural logarithm of earnings

S is the years of schooling

E is the years of working experience

E^2 is the square term of E

X is a vector of other wage determinants such as union membership and, socioeconomic characteristics.

Variables on income are typically represented in logarithm form (Shorrocks and Wan, 2004). There is a square term of E as the experience term is believed to have

non-linear effects ²¹ (Mincer, 1974). The regression-based decomposition methodology was proposed by Oaxaca (1973) and Blinder (1973) in the early 1970s to differentiate the causes of the wage differential into non-discrimination or discrimination factors. Later different kinds of decomposition approaches on decomposing different summary measures are invented by different researchers.

The Shapley Value decomposition proposed by Shorrocks (1999) is one of those approaches to quantify the contribution of each variable on total income inequality. Shapley value is a concept in game theory used for studying how to allocate fairly the gains obtained by cooperation among actors (Roth, 1988). The decomposition based on Shapley value is used to decompose income inequality by income component. The method involves extensive computation²². Lu and Zhao (2009) adopted this decomposition method to analyze the impact of social network to income determination and inequality among rural households. They find that the impact of social network on income inequality is greater in the eastern part of China than the middle and the western parts; Wan and Zhou (2005) also applied the same approach on household-level data to study the income inequality in rural China. It is found that capital input rather than geography becomes the most significant factor in affecting income inequality, while farming structure such as cropping pattern is more important than inputs such as labour in contributing to more inequality.

The method developed by Juhn, Murphy and Pierce (1991) is commonly adopted by researchers using the decomposition approach. In their work, wage differential

²¹ The age/earnings profile in Mincer (1974) and other studies show a quadratic functional curve, which supports the use of a square term in the earnings equation for investigation purpose.

²² For the theoretical set-up of the method, please refer to Shorrocks (1999).

between black and white people are decomposed into predicted and residual parts²³. Apart from Lui (2008) discussed in Chapter 2 which used this approach to decompose the variance of log wages, Blau and Kahn (1997) followed the approach of Juhn, Murphy and Pierce to study how the gender wage gap falls in tandem with unfavorable changes in wage structure to workers receiving low wages. They find supporting evidence on the notion that exceeding supply over demand hurts high skill female workers more than those middle-skilled and low-skilled.

Since the line of research using the decomposition approach originated from Oaxaca and Blinder and their methods constitute the main skeleton of the methodology in this thesis²⁴, the main idea and conceptual framework of their approach will be discussed in detail.

3.2.2 Oaxaca-Blinder Decomposition (OB Decomposition)

Oaxaca-Blinder decomposition (OB decomposition) is a commonly adopted method to decompose mean wage differential or changes into two kinds of effects by groups such as male versus female, immigrants versus natives, year 0 or year 1 and further divide the two effects into the contribution of covariates in a counterfactual manner (Borjas, 2000; Firpo, Fortin & Lemieux, 2007; Jann, 2008). The two effects are known as the wage structure effect and the composition effect²⁵. As explained by Chi, Li and Yu (2007), the wage structure effect is the effect on earnings due to differences or changes in returns to various labour market characteristics. For

²³ For the theoretical set-up of the method, please refer to Juhn, Murphy and Pierce (1991).

²⁴ More details will be discussed in Chapter 6.

²⁵ The wage structure effect and composition effect are named as coefficient effect and endowment effect respectively in some related studies (Jann, 2008).

instance, a higher return to higher education can raise the mean earnings of highly educated workers and thus the wage dispersion, since the wage dispersion among highly educated workers is typically larger; the composition effect is the effect on earnings due to differences or changes in distribution of labour market characteristics of workers within the population. For instance, a higher proportion of highly educated workers within a group can enlarge the wage dispersion between the two groups concerned. In some literature on wage discrimination such as Richard (2007), the wage structure effect is sometimes treated as the unexplained part which is considered to be the effect of discrimination on wage.

The first step of the OB decomposition involves the estimation of OLS coefficients of the two groups with the common Mincerian earnings equation as the basis²⁶. Suppose the two groups considered are workers in two different years, namely year 0 and year 1. Three wage vectors are needed to be defined, namely $\overline{Y_1}$, $\overline{Y_0}$ and $\overline{Y_c}$. Let $\overline{Y_1}$ be the mean wages of workers with both workers' characteristics and wage structure in year 1 which can be expressed as follows:

$$\overline{Y_1} = \overline{X_1}b_1$$

where $\overline{X_1}$ is the mean workers' characteristics in year 1

b_1 is the return to different labour market characteristics in year 1

$\overline{Y_0}$ is defined in the same manner. $\overline{Y_c}$ is the counterfactual mean wages of workers

²⁶ The conceptual framework discussed hereafter is based on Chi, Li and Yu (2007) with some modifications.

with workers' characteristics in year 1, but wage structure in year 0²⁷. The decomposition of differences in workers' mean wages across the two years can be done as follows:

$$\begin{aligned}
 \overline{Y_1} - \overline{Y_0} &= (\overline{Y_1} - \overline{Y_c}) - (\overline{Y_c} - \overline{Y_0}) \\
 &= (\overline{X_1}b_1 - \overline{X_1}b_0) - (\overline{X_1}b_0 - \overline{X_0}b_0) \\
 &= \overline{X_1}(b_1 - b_0) - b_0(\overline{X_1} - \overline{X_0})
 \end{aligned}$$

The first term captures the mean wage change due to the wage structure effect, while the second term captures the mean wage change due to the composition effect. The decomposition procedure can be conveniently carried out in econometric software such as STATA which only requires the implementation of the command **oaxaca** without constructing the counterfactual wage vector manually. Many researchers adopt this decomposition approach with some modifications to suit their needs. Chan, Sung, and Zhang (2001) discussed in Chapter 2 adopted the approach of Brown, Moon and Zoloth (1980) which extends the OB decomposition for the decomposition of wage differential into components due to intra-occupation wage differences and inter-occupation wage differences; Neuman and Oaxaca (1998) combined the OB decomposition procedure with Heckman procedure to correct for selectivity bias, which takes account of different probabilities of workers entering an industry. The proposed methodology is adopted to analyze wage differential by gender and between ethnicity in the Israeli labour market. It is found that discrimination is more important in explaining the gender wage gap than in explaining the ethnic wage gap.

²⁷ The counterfactual wage vector can be defined the other way round, i.e. mean wages of workers with workers' characteristics in year 0, but wage structure in year 1, depending on which group is chosen as the base year (Jann ,2008). Here manifest one of the shortcomings of OB decomposition which will be discussed in section 3.2.3.

3.2.3 Inadequacies of Decomposition Methods

Despite the wide application, many common decomposition methods have certain inadequacies in the study of wage dispersion. Taking OB decomposition for instance, many literatures have pointed out that results of decomposition are sensitive to the choice of reference group (Fortin, 2006; Firpo, Fortin and Lemieux, 2007a; Lui and Suen, 1998; Oaxaca and Ransom, 1999; Richard, 2007). In researches on discrimination, the choice depends on which group is taken as the non-discriminatory reference group (Jann, 2008). Nevertheless, the choice can sometimes be arbitrary. Many researchers have tried to deal with this problem with little adjustment to the procedures. Lui and Suen (1998) adjusted the specification by taking average to the information of the grouped data without choosing a reference group to analyze the wage differential between Hong Kong natives and immigrants²⁸. Fortin (2006) discussed various approaches developed by other researchers to tackle this problem of choosing a base group²⁹.

In addition, the application of OB decomposition “requires a parametric assumption about the form of the conditional expectation function” (Barsky, Bound, Charles and Lupton, 2002, p.663). Consistent estimates of the wage structure effect and the composition effect can only be obtained under the assumption of linearity in conditional expectation³⁰ (Firpo, Fortin and Lemieux, 2007a). Firpo, Fortin and Lemieux noted that using non-parametric reweighting method can tackle this

²⁸ For details, please refer to part IV in Lui and Suen (1998).

²⁹ For details, please refer to part 4 in Fortin (2006).

³⁰ A detailed discussion on this problem can be found in Barsky, Bound, Charles and Lupton (2002).

problem³¹. This is one of the procedures done in this thesis, which will be discussed more in the forthcoming chapters.

The last problem, which is the greatest, is that the conventional OB decomposition can only provide a simple mean comparison. It can only be applied on decomposing mean wages, which is unable to give a comprehensive picture of changes in wage dispersion. This is also an inadequacy of many other decomposition methods attempting to decompose summary measures such as variance. Decomposition on summary measures is limited to address complex changes in wage distribution, since the method can just offer an anatomy of the summary measures. With respect to the inadequacies of calculating summary measures or adoption of decomposition on summary measures, a new alternative, known as distributional approach, becomes more and more popular among researchers.

³¹ More account on non-parametric method will be discussed in Chapter 4.

Chapter 4

Distributional Approach

4.1 Background of Distributional Approach

As mentioned in the previous chapter, traditional approaches in studying wage dispersion have certain inadequacies. The calculation, comparison and decomposition of summary measures such as mean or variance are popular. Nevertheless, there are problems in the calculation of those indexes and as noted by Melly (2005), those piles of measures may give different weights on different parts of the distribution; giving rise to difference in inequality rankings; the decomposition methods such as the Oaxaca-Blinder decomposition provide a convenient way of decomposing changes or differences in mean wages into different effects of each covariate. Nonetheless, those common decomposition methods have certain flaws in manipulation and cannot give a clear picture of changes in wage dispersion over the whole wage distribution. Summary measures are often more suitable for usage when we want a convenient comparison on inequality rankings, while common decomposition methods can only offer an anatomy of the summary measures. For the sake of learning more about changes in wage dispersion arising from distributional changes, alternative approaches which consider the whole distribution instead of summary measures or mean is more appropriate in studying wage dispersion. As pointed out by Chi, Li and Yu (2007), the estimation of the entire wage distribution and decomposition of the changes in wage dispersion has been attracting the attention of labour economists. This is known as distributional approach. Comparing with traditional approaches, the distributional approach provides more

comprehensive information on wage dispersion (Chi, Li and Yu, 2007; Ginther, 2000). The shift in focus from aggregate changes to overall changes in the wage distribution over time can let researchers better target the location of changes in wage dispersion. Besides, distributional approach provides clearer indication of how wage changes of extremely high wage earners or extremely low wage earners can affect the wage dispersion. The study of Juhn, Murphy and Pierce (1993) is one of the forerunners in considering the whole distribution. It investigates the changes of the wage distribution across quantiles for finely classified skill groups. This study is commonly cited in many studies on wage distribution utilizing the quantile regression analysis, since it is an interim work between the traditional decomposition approach and the distributional approach.

In the next section, different methods under the distributional approach and related studies will be discussed. They range over parameterized techniques with tight assumptions at one end to loosely restricted non-parametric methods at the other end. Some involve quantile regressions dealing with median or other quantiles instead of mean estimation. Methodologies with extension of Oaxaca-Blinder decomposition at the mean to the whole distribution are also included within the category of distributional approach.

4.2 Estimation Frameworks: A Spectrum from Parametric Estimation to Non-parametric Estimation

A wide variety of estimation methods can be found in contemporary econometrics, ranging from parametric estimation at one end, semiparametric estimation in between,

to non-parametric estimation at the other end. As noted by Greene (2008, p.398), “the progression from full to semi to non-parametric estimation relaxes strong assumptions, but at the cost of weakening the conclusions that can be drawn from the data”. Adoption of parametric models such as maximum likelihood estimators is common. Härdle and Linton (n.d.) mentioned that the advantages of maximum likelihood estimators include the consistency in the estimated parameters of the likelihood function under the regularity assumption and the property of asymptotically normal distribution. Nevertheless, the costs of strong restriction imposition can be significant as misspecification of the functional forms or false setting of the model can offset the advantage of consistency. Thus much effort has been devoted in the development and utilization of non-parametric methods in different economic issues, with no exception to the study of wage dispersion. Researchers often include estimates from parametric methods for comparison with results from non-parametric methods. Ginther (2000) compared the relative suitability of adopting parametric and non-parametric estimates in the study of earnings inequality.³² The results show that nonparametric methods can pick up nonlinearities in earnings profiles, which is often ignored in previous research utilizing parametric approach. There are significant differences in the two estimation techniques, supporting the adoption of non-parametric methods.

Because of the benefits mentioned before, researches in wage dispersion based on non-parametric estimation are not uncommon. Ginther (2000) studied changes in earnings distribution of male workers in US from 1975 to 1994 based on specification of years of education and working experience. The results from

³² Two commonly used parametric frameworks, the Mincerian wage model and the Juhn, Murphy, and Pierce model, are chosen for comparison with non-parametric estimates. Details can be referred to part B “Are Nonparametric Methods Warranted?” in section III of Ginther (2000).

non-parametric regression support previous findings that there is a trend of increasing earnings inequality between and within groups; secondly, there is correlation between working experience and increases in returns to education; thirdly, workers earn more in real wage term in 1994 than similar workers in 1975 if they have sixteen years of education or more; fourthly, there is variation in the increases of within-group and between-group wage inequality at different points in the conditional distribution³³.

Barsky, Bound, Charles & Lupton (2002) examined the black-white wealth gap through a non-parametric method other than Oaxaca-Blinder decomposition which requires a parametric assumption on the form of distribution. The method reweights the empirical distribution of the dependent variable with weights that equalize empirical distributions of all independent variables. Apart from showing the inadequacies of the traditional Oaxaca-Blinder decomposition theoretically and empirically³⁴, Barsky *et al.* found that the wealth gap between blacks and whites can be accounted for by the divergence in the income distribution between blacks and whites households more than what was commonly believed. Besides, it is much more confirmed that the black-white wealth gap cannot be accounted by income differences only.

Semiparametric estimation is another popular estimation method in the study of wage distribution. It stands in the middle in the spectrum of estimation methods that range from parametric to non-parametric estimation. Powell (n.d., p.2444) defined semiparametric estimation as “a hybrid of the parametric and non-parametric

³³ Discussion on “conditional” and “unconditional” wage distribution and quantile regressions will be made in section 4.4.

³⁴ Discussion on inadequacies of Oaxaca-Blinder decomposition is made in section 3.2.2 in Chapter 3.

approaches to construction, fitting, and validation of statistical models”. As noted by Greene (2008), in comparison with parametric modeling, semiparametric estimation requires fewer assumptions. The distributional assumption is removed in general. Also, it is more robust than parametric approach. Studies on wage distribution using semiparametric approach are also popular.

Dinardo, Fortin and Lemieux (1996) adopted a semiparametric modeling to study the effects of institutional and labour market factors on changes in US wage distribution from early 1970s to early 1990s. They do so by controlling for the changes in real minimum wage, unionization level in percentage, distribution of workers’ characteristics and supply and demand of different workers’ groups and residuals. It is found that a large amount of increase in wage inequality can be attributed to de-unionization and supply and demand shocks. Minimum wage is also a significant factor in explaining increase in wage inequality, especially for women.

Since many other studies adopting the non-parametric or the semiparametric approach include the use of quantile regressions, they will be discussed together with the quantile regression technique in the following part.

4.3 Quantile Regressions and Decomposition

Mosteller and Tukey (1977) pointed out the inadequacy of traditional mean regression. Similar to the fact that mean cannot provide comprehensive information of a distribution, simple regression curve also cannot give complete details for an outcome distribution. Methods intended to give a series of regression curves

corresponding to different percentage points of the distribution emerge (Koenker, 2005). This is known as quantile regression approach. Among different researches on proposing quantile regression approaches, the method in Koenker and Bassett (1978) is the most popular and often being discussed or adopted in many studies on distribution (Otsu, 2008; Chamberlain, 1994; Buchinsky, 1994; Gosling, Machin and Meghir, 2000). Referring to the theoretical specification discussed in Buchinsky (1994), the quantile regression model proposed by Koenker and Bassett can be formulated as follows:

$$y_i = x_i' \beta_\theta + u_{\theta i} \text{ with } \text{Quant}_\theta(y_i|x_i) = x_i' \beta_\theta \quad (i=1, \dots, n)$$

β_θ and X_i are $K \times 1$ vectors, and $\text{Quant}_\theta(y_i|x_i)$ represents the θ th conditional quantile of y given x . Based on this basic theoretical specification or other similar approaches, various kinds of quantile regression modeling, from parametric at one end to non-parametric at the other end, are widely adopted in researches in labour economics including distributional changes in wage dispersion (Lu, Stander and Yu, 2003).

Chamberlain (1994) proposed two empirical approaches based on quantile regression for describing U.S. conditional distribution of wages thoroughly, with the first being utilized for studying changes of returns to schooling from late 1970s to late 1980s and the second for studying the relative wage effects of unionization in 1987. The first application shows that returns to education tend to increase uniformly from low to high quantile levels in both 1979 and 1987, with the returns significantly higher in 1987 than 1979; the second application shows that the decrease in positive union

wage effect from low to high quantiles for more experienced workers is larger than that for less experienced workers.

By using data from the German socioeconomic Panel from mid-1980s to mid-1990s, Fitzenberger and Kurz (2002) analyzed the earning structure in West Germany among different education and industry groups using quantile regressions. Firstly, it is found that the whole earnings distribution shifts over time in a uniform way that keeps the between- and within- groups earnings ratios constant; secondly, labour market characteristics have different effects on wages across quantiles³⁵; thirdly, there is a larger dispersion of earnings at higher quantiles across industries, which raises doubts on whether a uniform inter-industry earnings structure exists.

Buchinsky (1994) set up two quantile specifications, a simple one-group model as a variation of the Mincerian wage model and a 16-group model, for examining changes in returns to education and working experience across quantiles of the entire wage distribution in U.S. It is found that there is a difference in returns to education and working experience across quantiles. There is a manifest difference in wage inequality across skill groups.

There are a wide variety of researches combining the use of quantile regression with decomposition procedure and adopting a quantile-based decomposition approach for studying wage distribution. Gosling, Machin and Meghir (2000) set out models of the quantiles of the wage distribution in UK as functions of common labour market characteristics such as age, schooling, cyclical time effects and cohort effects,

³⁵ For detailed findings on this point, please refer to Fitzenberger and Kurz (2002).

followed by the decomposition of the overall increase in wage dispersion into effect from education and effect from cohort and age. The results show that roughly one-third of the rising wage inequality can be attributed to increases in educational differences, another one-third to continuous decrease in median wage growth rates of new labour cohorts, and the rest to within group effect. This is consistent across all education groups.

Machado and Mata (2005) is a popular study often being mentioned in other related studies on wage distribution. They analyze the distributional changes of wages in Portugal from mid-1980s to mid-1990s through the estimation of the marginal density function of wages in a particular year implied by counterfactual distributions of covariates. Through the comparison of different marginal distributions implied by different covariate distributions, it would be possible to produce counterfactual estimates of distributions. It is found that both changes in workers' characteristics and returns to these characteristics³⁶ lead to the increase in wage dispersion with the same magnitude. Education is the major factor contributing to rising wage inequality. The distribution of returns to schooling becomes wider and wider within the period under study. Besides, increase in educational level leads to a more unequal wage distribution. Machado and Mata have also made a brief comparison with alternative methods in similar researches. In comparison with the study of Dinardo, Fortin and Lemieux (1996) using the semiparametric approach, the method adopted by Machado and Mata is based on parametric modeling for conditional distributions and resampling procedures for obtaining the marginal distributions. In comparison with the study made by Gosling, Machin and Meghir mentioned in previous paragraph,

³⁶ The two factors correspond to composition effect and wage structure effect postulated in Oaxaca-Blinder decomposition framework.

both adopt quantile regressions for conditional distribution modeling. However, Machado and Mata believe that their method is simpler in the setting of unconditional distributions based on a conditional model³⁷.

Arulampalam, Booth and Bryan (2007) examined sectoral gender pay gaps across the entire distribution of wages in eleven European countries. The quantile regression framework of Buchinsky (1998) and the decomposition strategy of Machado and Mata (2005) are chosen as the empirical methodologies. The gaps measured vary significantly across different countries and wage distributions of public and private sector. It is found that the pay gap is typically wider at the top of the wage distribution, which is termed the glass ceiling effect, while in some country cases the gap is wider at the bottom, which is termed the sticky floor effect.

Lemieux (2002) suggested a unified approach which combines elements in several related studies such as Juhn, Murphy and Pierce (1993) and Dinardo, Fortin and Lemieux (1996) for decomposing distributional changes in wages³⁸. The procedure is an augmentation of common OLS estimation by logit or probit model, allowing reweighting to be done before the conduction of decomposition. The new approach is applied on analyzing differences in wage distribution in Alberta and British Columbia and changes in U.S. overall wage inequality³⁹. Besides, a comparison of the proposed approach and other decomposition methods is made⁴⁰.

Like the studies mentioned above, many other studies such as Melly (2005) and

³⁷ For deeper discussion, please refer to section 2.4 in Machado and Mata.

³⁸ Please refer to section 3 in Lemieux (2002) for the theoretical procedures.

³⁹ Since the focus of this paper is on proposing new methodology, results of the two applications will not be discussed in detail here. Please refer to section 4 and section 7 for results of the two applications.

⁴⁰ See section 8 in Lemieux (2002).

Melly (n.d.) adopted approaches within the spectrum of parametric to non-parametric modeling to perform quantile-based decomposition. Nevertheless, Firpo, Fortin and Lemieux (2007a) discussed different inadequacies of some popular methods mentioned above. The semiparametric approach of Dinardo, Fortin and Lemieux (1996) provided consistent estimation of wage structure effect and composition effect for any distributional statistics, but it is unable to further decompose the contribution of each factor into the two effects; the quantile-based decomposition procedures in Machado and Mata (2005) make the construction of counterfactual distribution and hence the computation of the overall composition effect and wage structure effect feasible. Nonetheless, the approach has a similar inadequacy of Dinardo, Fortin and Lemieux (1996). Further decomposition of overall composition effect into contribution of each factor cannot be done. Secondly, the implementation of the procedure is computationally difficult as a large number of quantile regressions and simulations are required to be done. Thirdly, like the case in Oaxaca-Blinder decomposition, misspecification problem would lead to inconsistency of decomposition estimation. Other methods such as that suggested in Juhn, Murphy and Pierce (1993) suffer similar inadequacies. In order to deal with some of these inadequacies, Firpo, Fortin and Lemieux proposed a new kind of distributional approach. Since their method is the core methodology adopted in this thesis, detailed discussion on their method will be made in the following section.

4.4 Firpo-Fortin-Lemieux Approach (FFL Approach)

4.4.1 Introduction

With the motivation mentioned in previous section, Firpo, Fortin and Lemieux

(2007a) developed a new kind of distributional approach involving two stages. Firstly, changes in wage distribution are divided into wage structure effect and composition effect without directly estimating a wage-setting model. This is done by doing a proper reweighting, either being achieved parametrically or non-parametrically, to obtain counterfactual wage vectors; secondly, novel recentered influence function (RIF) regressions⁴¹ are estimated on distributional statistics such as quantiles, variances or Gini to further decompose the two effects into contributions of each control variable, like what Oaxaca-Blinder decomposition approach does. This is done by simply replacing the dependent variable by corresponding RIF. Thus RIF regressions are easily computed as conventional OLS regressions. Firpo, Fortin and Lemieux adopted their approach to study how factors like de-unionization, education, occupation and industry changes lead to wage polarization of U.S. male workers within the period of late 1980s to mid-2000s. In brief, unions and schooling are most important in explaining changes of wage distribution over the investigated period. Also, different factors have effects with different magnitude on different positions of the wage distributions⁴². As mentioned in Chapter 1, there are three advantages of the FFL approach. Firstly, Like other methods in distributional approach, the FFL approach can allow researchers to “go beyond the mean” for studying wage dispersion; secondly, the procedures involved can be easily and systematically done, unlike other kinds of distributional approaches which may require multiple resampling or other computationally intensive procedures; thirdly, we can further divide the two effects into the contribution of each covariate on any distributional statistics of interest such as across quantiles, on variance or on Gini, unlike other methods which can only divide effects of covariates

⁴¹ Regression on recentered influence function (RIF) originates from Firpo, Fortin and Lemieux (2007b). For definition and properties of RIF, please refer to section 3 of Firpo, Fortin and Lemieux (2007b).

⁴² For details of the findings, please refer to section 5 in Firpo, Fortin and Lemieux (2007a).

into total wage structure effect or composition effect only. It is the third advantage which makes FFL approach superior to other methods under the distributional approach.

There are other studies which adopt the FFL approach. For example, Chi, Li and Yu (2007) adopted the approach to study the changes in urban income distributions in China in two time periods, one from 1987 to 1996 and the other from 1996 to 2004. Estimates from Oaxaca-Blinder decomposition is also made for comparison with the results from FFL approach. The results suggest that wage structure effects of gender, college education, industries, ownership of employers and regions contribute largely to the overall increases in income inequality. The effects of different factors vary at different positions of the wage distribution within different time periods. In the coming section, the conceptual framework of FFL approach will be covered.

4.4.2 Conceptual Framework

4.4.2.1 First Step: Reweighting

The essence of the first step resembles that in Dinardo, Fortin and Lemieux (1996). Effects of covariates on wage distribution are obtained by data reweighting. Firstly, weighting functions for group 1, group 0 and counterfactual, i.e. $\omega_1(T)$, $\omega_0(T)$ and $\omega_c(T, X)$ respectively where T represents treatment with the value 1 or 0 and $X \in \mathcal{X} \subset \mathbb{R}^K$, are estimated as follows (Firpo, Fortin and Lemieux, 2007a, p.11):

$$\omega_1(T) = \frac{T}{\bar{p}}, \quad \omega_0(T) = \frac{1-T}{1-\bar{p}} \quad \text{and} \quad \omega_c(T, X) = \frac{1-T}{\bar{p}} \times \frac{\bar{p}(X)}{1-\bar{p}(X)}$$

where $\hat{p} = N^{-1} \sum_{i=1}^N T_i$

$\hat{p}$ is “an estimator of the true probability of being in group 1 given X ”(Firpo, Fortin and Lemieux, 2007a, p.19), which is called the propensity score. This propensity score can be estimated either parametrically or non-parametrically⁴³. As mentioned in Firpo, Fortin and Lemieux (2007a, p.11), $\omega_1(T)$ and $\omega_0(T)$ “transform features of the marginal distribution of Y into features of the conditional distribution of Y_1 given $T = 1$, and of Y_0 given $T = 0$ ”, while $\omega_c(T, X)$ “transforms features of the marginal distribution of Y into features of the counterfactual distribution of Y_1 given $T = 1$ ”. Barsky, Bound, Charles and Lupton (2002) believed that it is unfeasible to analyze hypothetical distribution of black wealth conditional on white earnings function, which means analyzing the hypothetical distribution of the outcome variables of group 1 conditional on the covariate function of group 0 is impossible⁴⁴. However, Firpo, Fortin and Lemieux offer a way to do so in the first step. Kernel density estimation, a common non-parametric method in estimating the probability density function of a variable, can be adopted to illuminate the wage distributions of group 1, group 0 and counterfactual and hence allows analysis on the counterfactual. Nevertheless, as noted by some papers like Melly (2005), only focusing on counterfactual analysis may not be economically meaningful. The first stage estimation is a necessary step for doing decomposition on distribution, which will be discussed in the following section.

4.4.2.2 Second Step: RIF Regressions and Decomposition

⁴³ For the parametric approach and non-parametric approach in propensity score estimation, please refer to Appendix in Firpo, Fortin and Lemieux (2007a).

⁴⁴ Please refer to Barsky, Bound, Charles and Lupton (2002) for details.

After carrying out a reweighting procedure, RIF regressions on the distributional statistics ν_t and ν_C can be performed and regression coefficients τ_1^ν , τ_0^ν and τ_0^ν can be obtained (Firpo, Fortin and Lemieux, 2007a).

$$\begin{aligned}\hat{\gamma}_t^\nu &= (\sum_{i=1}^N \hat{\omega}_t^\nu(T_i) \times X_i \times X_i^T)^{-1} \times (\sum_{i=1}^N \hat{\omega}_t^\nu(T_i) \times \text{RIF}(Y_i; \nu_t) \times X_i) \quad t=0,1 \\ \hat{\gamma}_C^\nu &= (\sum_{i=1}^N \hat{\omega}_C^\nu(T_i, X_i) \times X_i \times X_i^T)^{-1} \times (\sum_{i=1}^N \hat{\omega}_C^\nu(T_i, X_i) \times \text{RIF}(Y_i; \nu_C) \times X_i)\end{aligned}$$

where $\text{RIF}(y; \nu_t) = \hat{\nu}_t + \hat{\text{IF}}(y; \nu_t)$ and $\text{RIF}(y; \nu_C) = \hat{\nu}_C + \hat{\text{IF}}(y; \nu_C)$ ⁴⁵

The above specifications on the coefficients imply that RIF regressions on weighted data is just like running weighted least square (WLS) regressions. The distributional statistics of interest can be on quantiles, variance or Gini. RIF regressions on quantiles are just like running quantile regressions but in unconditional sense. Firpo, Fortin and Lemieux (2007b) have a detailed discussion on unconditional quantile regression versus conditional quantile regressions (which is the kind of quantile regression commonly known). Conditional quantile regression is superior to OLS regression as it can let researchers “go beyond the mean” for studying distribution in a much more comprehensive way, as mentioned in previous section. However, Firpo, Fortin and Lemieux point out its disadvantage as follows:

Unlike conditional means, however, conditional quantiles do not average up to their unconditional population counterparts. As a result, the estimates obtained

⁴⁵ As defined by Firpo, Fortin and Lemieux (2007b, p.2), Influence function represents “the influence of an individual observation on a distributional statistics of interest”. Taking mean for instance, IF of mean is just the demeaned value of the outcome variable, which is $Y - \mu$.

by running a quantile regression cannot be used to estimate the impact of X on the corresponding unconditional quantile. (p.1)

For making it possible to estimate covariate effects on unconditional quantiles of an outcome variable, Firpo, Fortin and Lemieux proposed unconditional quantile regression based on RIF regressions across quantiles⁴⁶ and the new approach has been applied by some other studies on wage distribution (Boudarbat and Lemieux, 2007; Chi and Li, 2007; Chi, Li and Yu, 2007). After running RIF regressions across quantiles, on variance or on Gini, decomposition procedures resembling Oaxaca-Blinder decomposition can be performed as follows:

$$\begin{aligned}\bar{\Delta}_Y^Q &= (\sum_{i=1}^N \hat{\omega}_1(T_i) \times X_i) \times (\bar{Y}_1^Q - \bar{Y}_0^Q) \\ \bar{\Delta}_X^Q &= (\sum_{i=1}^N \hat{\omega}_1(T_i) \times X_i) \times \bar{Y}_0^Q - (\sum_{i=1}^N \hat{\omega}_0(T_i) \times X_i) \times \bar{Y}_0^Q\end{aligned}$$

where $\bar{\Delta}_Y^Q$ represents the wage structure effect; $\bar{\Delta}_X^Q$ represents the composition effect

In the next chapter, the background and descriptive statistics of the data used in this thesis will be discussed.

⁴⁶ Firpo, Fortin and Lemieux discussed the supremacy of unconditional quantile regression over conditional quantile regression in studying wage inequality based on the study of Chamberlain (1994). For details, please refer to Firpo, Fortin and Lemieux (2007b).

Chapter 5

Data Description

5.1 Data Background

The data sources in this thesis are the population census datasets acquired from the Hong Kong Census and Statistics Department, including 1981 census 1% sample dataset, 1986 by-census 1% sample dataset, 1991 census 5% sample dataset, 1996 by-census 5% sample dataset, 2001 census 1% sample dataset, 2006 by-census 1% sample dataset. The use of the six cross-sectional census datasets is for investigating the changes in wage dispersion from 1980s to mid-2000s. The Hong Kong Population Census is held every ten years and the By-census is carried out in between every two censuses. Within each dataset, individual records comprise of three elements, namely quarters, households and persons. Only the person records will be used for analysis in this thesis⁴⁷. According to the user guides of the datasets (Hong Kong Census and Statistics Department, 2007a; HKCSD, 2002; HKCSD, 1997; HKCSD, 1992), the initial samples of all the censuses and by-censuses do not strictly follow EPSEM⁴⁸. The sampling fractions vary across different districts and so different weighting factors are utilized for the estimation. Nevertheless, proper action has been taken by the department statisticians so that all quarters have an equal chance of being selected.

Many studies of Hong Kong in labour economics such as Chan, Sung and Zhang

⁴⁷ For the number of records in all six census years, please refer to table 1 in Appendix.

⁴⁸ EPSEM (Equal Probability of SElection Method) is a principle of selecting sample so that every case within the population is equally probable to be chosen (Healey, 2005).

(2001), Ng (2001), Lui (2008), Lui and Suen (1998) chose to use census and by-census datasets for analyses. There are two main advantages in this choice. Firstly, the data are collected officially by the government which is highly reliable and representative; secondly, there is rich information relevant for the research purpose in this thesis. Data of common socio-demographic characteristics such as education and age are obtainable. Although different enumeration approaches were adopted for data collection in different census years, figures in different datasets are widely comparable⁴⁹ (Hong Kong Census and Statistics Department, 2007a; HKCSD, 2002; HKCSD, 1997; HKCSD, 1992). In the coming section, treatment on the raw census data for research purpose will be discussed.

5.2 Data Treatment

In this thesis, only socio-economic data relevant to the proposed study are considered.

They are outlined as follows:

- *gender*
- *marital status*
- *place of origin*
- *age*
- *education*
- *industry of work*
- *occupation of work*

⁴⁹ The department adopted the de facto approach to enumerate residents present in Hong Kong for the 1996 by-census and those beforehand and adopted the “resident population” approach for 2001 census and 2006 by-census. Details can be referred to the user guides of the population census datasets in different census years.

The data of the above characteristics each with a different coding are transformed to binary dummy variables based on their individual classification of groups. They are outlined as follows:

- 1 gender dummy: *male*
- 3 marital-status dummies: *nomarr*, *spouse*, *marrbef*
- 3 place-of-origin dummies: *native*, *chiim*, *overseaim*
- 5 age dummies: *age1525*, *age2635*, *age3645*, *age4655*, *age5665*⁵⁰
- 7 education dummies: *pri*, *f3*, *f5*, *f7*, *postsec*, *undergrad*, *postgrad*
- 8 industry dummies: *priin*, *manu*, *egw*, *cons*, *wrtch*, *tsc*, *finance*, *socser*⁵¹
- 6 occupation dummies: *priwork*, *manager*, *pro*, *clerk*, *service*, *secwork*⁵²

Table 3 in the Appendix shows the definitions of the variables. Hourly wage is more appropriate to be chosen for labour market analyses. Nevertheless, since the census datasets have no information on hourly wages or the number of working hours, the individuals' monthly income from main employment will be used instead⁵³. On the other hand, though wage data in either real or nominal term does not matter so much for the study of wage dispersion, getting rid of the effect of price factor on affecting the wage level is important in focusing on the effect of labour market factors only. In addition, appropriate comparison across different census years require the wage data to be converted into real terms. Thus the wage data are adjusted for inflation with

⁵⁰ There are only five age dummies with age ranging from 16 to 65. This is due to the restriction set for including the active labour force only. More discussion on the sampling criteria will be discussed soon.

⁵¹ For detailed classification, please refer to Appendix I in 2006 dataset userguide.

⁵² For occupations included in the individual variables, please refer to table 2 in the Appendix; for detailed classification, please refer to Appendix II in 2006 dataset userguide.

⁵³ Data on monthly wage will be taken the natural log form for analysis. The reasons will be mentioned in chapter 6.

1981 as the base year and so real wages are used for analysis⁵⁴. This is a common practice among labour economists, for better comparison of changes in workers' real purchasing power (Ehrenberg and Smith, 2006).

Since data on actual working experience is unavailable in census datasets, potential working experience, defined as *age* minus *agelfsh*, is calculated as a substitute of actual working experience. *agelfsh* is the age when the workers finish their schooling. This way of calculating potential working experience is different from the common practice of subtracting age by years of schooling and the value 6, i.e. *age* minus *schooling* minus 6⁵⁵ (Boudarbat and Lemieux, 2007; Lui and Suen, 1998; Ng, 2001). The latter approach requires information on years of schooling. However, since the census datasets only provide the workers' highest level of educational qualification, *agelfsh* is calculated instead, which should be equal to *schooling* plus 6 in theory. *agelfsh* is found by making inference from the corresponding appropriate year of obtaining the highest level of educational qualification⁵⁶. Two assumptions are made for constructing the continuous variable *agelfsh* from the nominal variable educational qualification. Firstly, it is assumed that once a person obtains a particular educational qualification, he or she would choose not to continue human capital investment at school and quickly find jobs in the labour market; secondly, as children under the age of 15 are legally prohibited from work in Hong Kong according to the Employment of Children Regulations (Labour Department of HKSAR, 2008) and the usual education level for a Hong Kong 15-year-old child is Form 3, it is assumed that

⁵⁴ Chart 1 in the Appendix shows the composite CPI index from 1981 to 2008. The prices of goods and services were increasing from 1980s to 1990s. However, there was a short-period slight decrease from the peak level from late 1990s and the CPI increased again after SARS. The prices of goods and services after mid-1990s are almost three times that in early 1980s.

⁵⁵ Subtraction of the value six implies an implicit assumption that workers started to receive education when they were six years old.

⁵⁶ Table 4 in the Appendix provides more details.

all people who have educational qualifications of Form 3 or below started their career life at 15 years old.

In this thesis, some basic criteria are set for case selection. Firstly, workers other than employees are excluded as they may not be earning labour income. For example, entrepreneurs as employers earn profit and not wages. Secondly, for the purpose of studying labour wages, only those aged between 15 and 65 are included within the sample for analysis; thirdly, those with monthly income at zero⁵⁷ or not available are excluded as the natural logarithm of zero would produce errors; fourthly, only Hong Kong natives or Chinese immigrants are included for analysis as foreign workers may have different earnings patterns which may cause possible bias in the results (Education and Manpower Bureau, 1999); fifthly, those with occupation not applicable or working experience less than zero are excluded from negatively affecting the estimated results; The cases left after the sample restriction process can then be used for analysis⁵⁸. In the coming section, discussion on the socio-economic characteristics of the sample over years will be discussed.

5.3 Statistical Portrait

Table 5a and Table 5b in the Appendix display the socioeconomic characteristics of the samples in all the six census years. The mean age of workers is increasing over decades, showing that our work force gets older and older. The continuous increase in mean age is associated with the increase in the working experience of the work force. It is not counter-intuitive that the older a person is, the more the working

⁵⁷ Those cases with very high earnings are top-coded in the census datasets, possibly for confidentiality reason. They are recoded as zero in this study and so being excluded for analysis.

⁵⁸ The number of “eligible” cases for use can be found in Table 1 in the Appendix.

experience he or she would have. On the other hand, the proportion of female workers within the labour force is increasing over decades. This reflects a higher degree of female worker acceptance by our labour market.

Regarding the place of birth, the proportion of natives and that of Chinese immigrants in the population are similar in early 1980s. Nonetheless, the proportion of natives in the population kept increasing in tandem with the continuous decrease in the proportion of Chinese immigrants. By the early 2000s the proportion of natives within the work force is more than two times that of Chinese immigrants. One possible reason may be that many of those who had come to Hong Kong in early 1950s or 1960s, who probably accounted for a large proportion of early Chinese immigrants, feared about the hand-over of Hong Kong sovereignty to mainland China in 1997s and emigrated abroad.

Considering educational level, workers who received primary education only accounted for almost half of the work force in early 1980s. However, the educational level of our work force is upgrading and people with F5 qualification accounted for the largest proportion in 2006. The increase in proportion of workers holding undergraduate degree is the largest.

The changes in proportion of workers' industry and occupation affiliation somehow manifest a rough picture of Hong Kong's economic restructuring since 1980s. In the early 1980s, manufacturing industry still prevailed and employed almost forty percent of the workforce in the sample. Nevertheless, we lost our comparative advantage in manufacturing due to the opening up of the mainland China with its low

cost land and labour. The manufacturing workforce started to shrink in size and the percentage dropped to a single digit figure in 2006. In the meantime, service industries such as *wrtrh*, *tsc*, *finance* and *socser*⁵⁹ is growing and employ higher and higher proportion of labours. Up to 2006, *wrtrh* and *socser* employ the largest proportion of work force in the sample, followed by *finance* and *tsc*. Regarding occupation, the largest proportion of labour force worked as secondary workers in early 1980s. Service workers account for the second largest proportion. Over the decades, fewer and fewer people worked as secondary workers and the proportion dropped by almost forty percent by 2006. Service worker is now the occupation which accounts for the largest proportion, followed by professional and clerk. This is a common situation among service-oriented or knowledge-based economies.

Table 6 in the Appendix shows the central tendency and dispersion of workers' wages in all six census years. The mean wage in nominal terms increased almost 2-fold every five years. Nevertheless, the rate of increase was not so salient from mid-1990s, possibly due to the deflation in late 1990s⁶⁰. The nominal mean wage even decreased slightly from 2001 to 2006, though there was a small rebound in prices. The mean wage in real terms has a similar pattern of change. All the inequality measures in the table are calculated based on real wage with 1981 as the base year. The wages at lower level, middle level and higher level, represented by the wage levels at the 10th, the 50th and the 90th decile respectively, have all been increasing during the twenty years since early 1980s. Nonetheless, the wages at the 10th, the 50th and the 90th decile decreased from 2001 to 2006, which is consistent

⁵⁹ *wrtrh* represents the sector of wholesale, retail and import/export trades, restaurants and hotels; *tsc* represents sector of transport, storage and communication; *finance* represents sector of financing, insurance, real estate and business services; *socser* represents sector of community, social and personal services.

⁶⁰ For the trend of price change over years, please refer to Chart 1 in the Appendix.

with the result shown by the HKCSD thematic report on income distribution⁶¹. The Gini Coefficient, the popular inequality measure, increases continuously since the early 1980s. This is the same for other inequality measures namely relative mean deviation and the Theil Coefficient. Nevertheless, the coefficient of variation decreased in value from 1996 to 2001, which is contradictory to the situation of other measures. As discussed in Chapter 3, this is due to different weights attributed to the different positions of the wage distribution by different inequality measures. The values of those measures are lower than those for the same year reported in the thematic report, as the values in the report are measuring the household income dispersion, which should be larger than the wage dispersion since income other than labour income are also counted for calculation. Regarding the quantile ratios, the 90-10 ratio generally increases over years except from 1986 to 1991, showing a general increase in wage dispersion between the high wage earners and the low wage earners. For the situation of wage dispersion between the high wage earners and middle wage earners, the 90-50 ratio generally increases over years except the slight decrease from 1991 to 1996. The situation of wage dispersion between the middle wage earners and the low wage earners varied over years, but in general it increases since 1980s. In the next chapter, the practical aspect of the research methodology adopted in this thesis will be discussed.

⁶¹ Discussion on the thematic report has been made in Chapter 2.

Chapter 6

Research Methodology

For studying the changes in wage dispersion of Hong Kong, both Oaxaca-Blinder decomposition based on OLS estimates and FFL approach involving reweighting, RIF regressions and decomposition will be adopted. The mean estimates from Oaxaca-Blinder decomposition provide a preliminary overview of changes in wage dispersion, while estimates from FFL approach give a more comprehensive picture. All the regressions will be run by using STATA, a powerful statistical package in data analysis. In the coming section, the modeling of Oaxaca-Blinder decomposition will be discussed first.

6.1 Set-up of Oaxaca-Blinder Decomposition

Firstly, a simple structural model based on Mincerian wage model is specified as follows:

$$\begin{aligned}
 \ln wage_t = & \alpha_t + \beta_1 male_t + \beta_2 spouse_t + \beta_3 marrbef_t + \beta_4 chiim_t \\
 & + \beta_5 age2635_t + \beta_6 age3645_t + \beta_7 age4655_t + \beta_8 age5665_t \\
 & + \beta_9 f3_t + \beta_{10} f5_t + \beta_{11} f7_t + \beta_{12} postsec_t + \beta_{13} undergrad_t \\
 & + \beta_{14} postgrad_t + \beta_{15} manu_t + \beta_{16} egw_t + \beta_{17} wrtrt_t + \beta_{18} tsc_t \\
 & + \beta_{19} finance_t + \beta_{20} socser_t + \varepsilon_t
 \end{aligned}$$

The data of real wage is taken the natural log form⁶². Variables on experience are excluded as they are not highly reliable. Firstly, they are self-created variables from other data and there can be calculation errors. Also, assumptions made for the creation of experience variables are strong that undermine the accuracy of regressions with the inclusion of them⁶³. Age dummies will be used instead as age variables can capture the effect of life experience which may contribute to higher marginal product other than working experience. Besides, education dummies are used instead of years of schooling. Apart from unavailability of data on years of schooling, the avoidance of imposing linearity assumption on the effect of education is another reason for using education dummies (Skalli, 2007). Different levels of education can have different effects on wages. The utilization of dummies can better capture the non-linear effect of education on wages. On the other hand, occupation variables are excluded as there can be collinearity problem between education and occupation variables, which would bias the estimation result⁶⁴. To avoid dropping into dummy variable trap, *nomarr*, *native*, *age1525*, *pri* and *cons* are excluded from the wage model⁶⁵.

Six Mincerian wage regressions will be run for all census years and mean decomposition between two groups of samples in different years will be done as follows (Chi, Li and Yu, 2007):

$$\overline{Y_1} - \overline{Y_0} = b_1(\overline{X_1} - \overline{X_0}) + \overline{X_0}(b_1 - b_0)$$

⁶² The reason has been discussed in Chapter 3.

⁶³ For example, female workers may leave the labour market for long-period maternal leave.

⁶⁴ The data does show certain degree of aggregation of occupation by education, which is unsurprised. Most of the higher educated workers are managers or professionals, while there is a higher proportion of the lower educated workers as secondary workers.

⁶⁵ The industry dummy *prim* is also excluded automatically since most of the people working in this sector are self-employed. The step of excluding labour force other than employees also excludes a very large amount of self-employed people in the primary sector.

where $\overline{Y_1}$ & $\overline{Y_0}$ are mean wages in year 1 and year 0 respectively

$\overline{X_1}$ & $\overline{X_0}$ are average characteristics of workers in year 1 and year 0 respectively

b_1 & b_0 are returns to various labour market characteristics in year 1 and year 0 respectively

By doing so, the changes in mean wage across years can be studied. Nevertheless, studying changes in mean wage can only give a general picture of changes in wage dispersion. The FFL approach will be adopted for studying changes in the entire distribution.

6.2 Set-up of FFL Approach

In the first step, the propensity scores of being in year 1 conditional on sample characteristics of year 0 are estimated first. As mentioned in Chapter 4, the propensity score can be estimated either parametrically or non-parametrically. This thesis chooses the parametric approach to estimate the propensity scores. A probit model for the estimation of propensity score is set up as follows (Studenmund, 2001):

$$\begin{aligned}
 F^{-1}(P_t) = & \alpha_t + \beta_1 \lnrwage_t + \beta_2 male_t + \beta_3 spouse_t + \beta_4 marrbef_t \\
 & + \beta_5 chiim_t + \beta_6 age2635_t + \beta_7 age3645_t + \beta_8 age4655_t \\
 & + \beta_9 age5665_t + \beta_{10} f3_t + \beta_{11} f5_t + \beta_{12} f7_t + \beta_{13} postsec_t \\
 & + \beta_{14} undergrad_t + \beta_{15} postgrad_t + \beta_{16} manu_t + \beta_{17} egw_t
 \end{aligned}$$

$$+\beta_{18}wrtr_{it} + \beta_{19}tsc_{it} + \beta_{20}finance_{it} + \beta_{21}socser_{it} + \varepsilon_{it}$$

where P_{it} is the probability of $yr_{it}=1$

F^{-1} is the inverse of the normal cumulative distribution function

The specification above is the same as that of the Mincerian wage model except the inclusion of natural log real wage. After estimating the propensity scores for each partner group of years, reweighting factors based on the specification stated in Chapter 4 are calculated manually. The wage functions are reweighed by multiplying with the reweighting factors to obtain the counterfactual wage vectors. Kernel density estimation will be conducted to extrapolate the wage vector in year 1, the wage vector in year 0 and the counterfactual wage vector to the entire population. The advantages of this non-parametric approach are that “it omits both the problem of arbitrary income interval framing and discounts the problematic classification into categories for histograms” (Schmidt, 2002, p.8) and the approach is widely adopted for estimating unknown density function (Schmidt, 2002; Jenkins, 1995; Dinardo, Fortin and Lemieux, 1996).

After obtaining the counterfactual wage vectors by reweighting, the second step of running RIF regressions on the wage vector in year 1, the wage vector in year 0 and the counterfactual wage vector across quantiles (unconditional quantile regressions), will be performed. To capture the rich pattern of changes in the wage distribution in different year pairs, the log wage changes at nineteen different wage vigintiles, from the 5th to the 95th vigintile equally spread over the whole wage distribution, are decomposed. Focusing on vigintiles instead of quartiles or any other kinds of

quantiles can enable us to see the different impacts of different factors at sufficient amounts of points of the wage distribution. The specification of RIF regressions is the same as that of Mincerian wage model. Total effects, Wage structure effects and composition effect are obtained by subtraction of coefficients as follows:

Total effect: $\beta_1 - \beta_0$

Wage structure effect: $\beta_1 - \beta_c$

Composition effect: $\beta_c - \beta_0$

In the next chapter, the empirical results will be presented and discussed.

Chapter 7

Empirical Results

As mentioned in the previous chapter, the results from the conventional Oaxaca-Blinder decomposition provide a preliminary overview of changes in wage dispersion, while the results from the FFL approach give a more comprehensive picture. The base group is those non-married native female workers aged between 15 and 25, who have primary school qualification and work in the construction sector. The results from the OB decomposition will be discussed first.

7.1 Results of OB Decomposition

7.1.1 OLS Estimates

OLS estimation is the necessary step for performing OB decomposition. Table 7 in the Appendix presents the OLS estimates of Mincerian wage models (mean estimates) for all census and by-census years. The results provide a general picture of the changes in the wage structure of the Hong Kong labour market since 1980s. Most coefficients are highly statistically significant. The mean gender wage gap has narrowed from 1981 to 2006, as shown by the continuous decrease in the value of the estimated coefficient of *male*. In the meanwhile, the coefficient estimates of *chiim* become more and more negative from 1981 to 2006, implying the mean wage gap between natives and Chinese immigrants has widened. All of these results support the findings of some previous studies⁶⁶.

⁶⁶ Please refer to section 2.2 for the discussion.

The accumulation of human capital stock is associated with an increase in working experience or age. It is not counter-intuitive that when a worker gets older, he or she would get higher wages and then receive less beyond a certain age since the depreciation of human capital stock outweighs investment. Another possible explanation is the delayed compensation in the earnings profiles of employee as a HR management tool. Nevertheless, in 1981, the mean returns to age decreases monotonically, as shown by the smaller and smaller values of coefficients from the low age cohort dummy to the high age cohort dummies. Only from 1986 onwards, it is curvilinear, first increases up to the age group of 36-45 and then decreases above 46, showing a concave life-time earning profile with a peak within the 36-45 age group. In general, the returns to all age groups have increased considerably from 1981 to 2006⁶⁷. For education, it is not surprising to find that the mean return to education increases with higher education. The mean returns to all education groups generally increase since 1981. This can be due to the China's opening up which led to the expansion of manufacturing sector in the mainland. This created demand on HK talents and so raised their returns to education. Nonetheless, the mean returns to all education groups decrease from 2001 to 2006, since Hong Kong owned manufacturing expansion in China hit a wall by the late 1990s. In the meantime, the increase in the labour demand for higher educated workers was not as salient as before starting from early 2000s, a post-Asian Financial Crisis period in which various unfavourable events such as SARS occur and hit the economy seriously. Lui (2008) suggested that the increase in the supply of workers with postsecondary education or above was larger than the amount of increase in demand, which resulted in a decline in the wage premium for those workers. The economic downturn may

⁶⁷ The exception is the decrease of return to *age2635* from 1986 to 1991 and from 1991 to 1996.

play a role in decreasing the rate of increase in the demand on highly educated workers.

Considering industry, the mean returns to *manu* and *egw* increase continuously from 1981 to 2006. The manufacturing sector becomes less and less significant in Hong Kong due to its comparative disadvantages compared with nearby economies. Those companies still surviving are highly competitive and the sector shifts from labour-intensive to more skill-intensive, leading to higher returns to *manu*. The mean returns to *wrtrh*, *tsc*, *finance* and *socser* increase from 1981 to 1986, but decrease from 1986 onwards and the former three have a slight increase from 2001 to 2006. The four sectors employ larger and larger proportion of workers and so decreases the mean returns to workers in those sectors. In the post-Asian financial Crisis period, many workers in various sectors got fired and those left behind were highly competitive and so the returns to those sectors (*wrtrh*, *tsc*, *finance*) increase.

7.1.2 Mean Decomposition

Decomposition on the OLS mean estimates is performed for the five year pairs. Table 8 to 12 in the Appendix presents the results of the conventional OB decomposition of mean wage change from 1981 to 2006. The contribution of each specific variable to the composition effect and the wage structure effect on mean wage change are shown. For most year pairs, the wage structure effect accounts for a larger proportion of total log wage change than the composition effect. Besides, both the composition and the wage structure effect are always positive in all year pairs except from 2001 to 2006. The wage structure effect on mean wage change is negative within that period. The

changes in returns to different characteristics shown in Table 7 are the hints on explaining the signs and changes of the wage structure effect, while the changes in composition of different characteristics shown in Table 5 are the hints on explaining the signs and changes of the composition effect.

The continuous decrease in the percentage of male workers and the return to males exert negative composition and wage structure effects on change in mean wage respectively⁶⁸. Since male workers generally have wage premium over female workers, the decrease in the proportion and return to this group with wage premium would lower the mean wage of the whole group of workers. In the meantime, the continuous decrease in the percentage of immigrant workers and the return to immigrants exert positive composition and negative wage structure effects on the change in mean wage. Since Chinese immigrant workers generally earn less than native workers, the decrease in their proportion would increase the mean wage of the whole group of workers, while the decrease in return would lower the mean wage.

The results for the factor of age are sensible. For example, from 2001 to 2006, the proportion of workers aged between 36 and 45 decreases from 30.52% to 29.39%⁶⁹. This decrease in the proportion exerts a negative composition effect and decreases the mean wage of the whole group of workers. In the meanwhile, the 7.3% increase in the return to *age3645*, as shown in Table 7, exerts a positive wage structure effect and increase the mean wage. Considering the factor of education, the decomposition results show that all education dummies exert positive composition and wage structure effect on change in mean wage in 1980s (from 1981 to 1986 and from 1986

⁶⁸ The exception is the positive wage structure effect from 1996 to 2001.

⁶⁹ Please refer to Table 5.

to 1991). Both the increase in the proportion of workers with F3 level or above and the increase in returns to education have an effect on increasing the mean wage. From 2001 to 2006, since the mean returns to all education groups generally decrease, all education levels exert negative wage structure effect which counteracts the positive composition effect. When both effects are taken into account, only education levels of undergraduate or above have an overall effect of increasing the mean wage.

Considering the effect of industry, only the effects of *manu* and *finance* are considered here as they are the major industries in contributing to the economic success of Hong Kong economy in different periods. The manufacturing sector always has a positive composition and wage structure effect on change in mean wage. The manufacturing workers earn less than the construction workers within the investigation period. The decrease in the proportion of manufacturing workers in the labour force has an effect of raising the mean wage. At the same time, the elimination of low productivity jobs in manufacturing increases the mean wage. From 1986 onwards, *finance* exerts a positive composition effect as the finance sector started to grow and finance workers command a wage premium over construction workers. Nevertheless, the return to finance workers decreases due to larger supply in the market and so *finance* exerts a negative wage structure effect on mean wage. Comparing the overall effect of *manu* and *finance* on change in mean wage, the effect of *manu* is larger and the situation reverses from 2001 to 2006. The financial sector becomes more significant in raising the mean wage.

7.2 Results of FFL Approach

7.2.1 1st step: Reweighting and Kernel Density Estimation

The first step in the FFL approach is a reweighting procedure for generating a counterfactual wage vector. The kernel density estimation, a common non-parametric method, is used to extrapolate the data to the entire population and provides a quick glance on the dispersion of wage distribution in different years. Jenkins (1995) also used kernel density estimation to study the changes in the middle income accumulation in the United Kingdom during the 1980s. Figure 1 in Appendix shows the kernel density estimations of the wage distribution for all census and by-census years since 1981. The distribution continues to shift rightwards year after year, showing a continuous general improvement in workers' wage. Nonetheless, the magnitude of shift becomes smaller and smaller and the shift of wage distribution from 2001 to 2006 is slightly leftward. This implies that real wage improvement since 1980s becomes less and less significant and there is a backward real wage change since 2000s.

Figure 2 to 6 in the Appendix show the kernel density estimations of wage distribution in each year pair and the counterfactual wage distribution. The three density plots in each figure represent three wage distributions with different characteristics as follows:

	Distribution of characteristics in which year?	Wage structure in which year?
Distribution in year 1	Year 1	Year 1
Distribution in year 0	Year 0	Year 0
Counterfactual distribution	Year 1	Year 0

Taking the year pair of 1981vs1986 for instance, the counterfactual distribution is

thus the wage distribution of workers with distribution of characteristics in 1986 but wage structure in 1981. By comparing the wage distribution in 1981 and the counterfactual distribution, we can get an idea of how changes in the distribution of workers' characteristics, i.e. the composition effect, has affected the wage distribution by keeping the wage structure fixed; by comparing the wage distribution in 1986 and the counterfactual distribution, we can get an idea of how changes in the wage structure of workers, i.e. the wage structure effect, has affected the wage distribution by keeping the distribution of workers' characteristics fixed. The effect on mean wage can be depicted by the shift in the position of the top, while the effect on wage dispersion can be depicted by the change in the width of the distribution. In Figure 2, it is shown that the composition effect increases the mean and shifts the wage distribution in 1981 rightwards to the position of the counterfactual plot, implying that the composition effect on the mean is positive. Nevertheless, the wage structure effect shifts the counterfactual distribution leftwards to the position of the 1986 plot, implying the wage structure effect on mean wage is negative. Thus the positive composition effect and the negative wage structure effect together shift the wage distribution in 1981 to the position of the 1986 plot. In addition, the dispersion of wage gets wider than that in 1981 as shown by the wider counterfactual distribution, and the 1986 distribution is narrower than the counterfactual one. These imply that the composition effect and the wage structure effect on wage dispersion are positive and negative respectively. From the kernel density plots in year pairs of 1981vs1986, 1986vs1991 and 1991vs1996 in Figure 2, 3 and 4, it is found that the composition effect and the wage structure effect are always positive and negative on mean wage and wage dispersion in each year pair. The wage structure effect on mean wage found without estimating a wage model here is opposite to the results in OB

decomposition. Referring to Figure 5, from 1996 to 2001, both effects on mean wage are positive, while the composition effect and the wage structure effect on wage dispersion are positive and negative respectively. Referring to Figure 6, from 2001 to 2006, both effects on mean wage are the same as that in year pairs before 1996. Nevertheless, it is difficult to determine the direction of the two effects on wage dispersion from reading the density plots. A clearer picture of the situation from 2001 to 2006 and more detailed account on the direction of the two effects on wage dispersion with model estimates as the basis will be given in section 7.2.3.

7.2.2 2nd step: RIF Regressions across Quantiles

After performing the reweighting procedure and obtaining the counterfactual wage vectors, the second step of running RIF regressions on the wage vector in year 1, the wage vector in year 0 and the counterfactual wage vector across quantiles will be performed. The quantile estimates provide more information than the OLS estimates by showing the wage determination and structure at the different wage levels. “At any chosen quantile we can ask, for example, how different are the corresponding [wages of males and females], given a specification of the other conditioning variables” (Hallock and Koenker, 2001, p.149). Table 13 to 18 in the Appendix show the unconditional quantile regression estimates at the 10th, 50th and the 90th decile in all census and by-census years since 1980s⁷⁰. The tables provide a quick glance of the values and degree of significance of all coefficients at the three specific deciles. Most of the coefficient estimates are highly statistically significant, with a few exceptions for occupation dummies. In general, the coefficient estimates at upper

⁷⁰ The results of unconditional quantile regression estimates on counterfactual wage are not included in Appendix.

quantiles are more statistically significant than those at lower quantiles. Also, the values of the adjusted R-bar Squared are higher at upper quantiles. These imply that the model specification can explain the wage structure at upper quantiles better than at lower quantiles.

Apart from tables, some graphs of the quantile estimates, are also included in the Appendix (Figure 7 to 12). We have twenty variables and one constant term and so there are twenty-one coefficients. For each coefficient, nineteen distinct quantile regression estimates for τ ranging from 0.05 to 0.95 are plotted. In each plot the horizontal axis represents the quantile τ and the vertical axis represents the covariate effect. The constant term of the model can be interpreted as the estimated unconditional quantile function of the wage distribution of those non-married native female workers aged between 16 and 25, with primary school qualification and work in the construction sector. The graphical display of quantile estimates can provide a more detailed picture of the covariate effect across quantiles compared with the utilization of tables, since more estimates at different quantiles can be shown in a concise manner.

Considering gender, Figure 7 to 12 show that the estimates of *male* generally decrease from lower to upper quantiles, implying that the gender wage gap decreases from lower to upper quantiles and the status of gender plays a more important role in determining wage levels for low wage earners. Many low wage earners work in labour-intensive industries such as the construction sector which emphasize more on physical strength and so benefit male workers. Nevertheless, high wage earners often work in skill-intensive industries such as the financial sector. The status of gender

does not matter in this case and so does not give rise to wage differential as significant as that at the lower quantiles. Referring to Table 13 to 18, by comparing the values of the coefficients of *male* at different quantiles in different years, it is found that the gender wage gap at the low quantile level (10th) has narrowed from over 40 percent in the 1980s to below 40 percent since 1990s, while that at the middle quantile level (50th) also narrows from over 30 percent in 1980s to below 30 percent since 1990s. The gender wage gap at upper quantile level (90th) fluctuates within the range of ten percent to twenty percent. This implies that the status of gender becomes less and less important in determining the wage levels of workers at middle quantile levels or below. A possible reason can be the higher demand of “mental skills” in the labour-intensive industries. However, the gender wage gaps at lower quantiles are still higher than those at upper quantiles. In section 7.1.1, it is mentioned that mean gender wage gap has narrowed from 1981 to 2006. From the results of RIF regressions across quantiles, we can attribute this phenomenon to the narrowing of gender wage gap among low wage earners.

For marital status, much literature in labour economics has noted that there is wage premium for married workers or workers married before over those unmarried (Lui and Suen, 1998). From Figure 7 to 12, it is shown that the effect of *spouse* and *marrbef* increases from lower quantiles to upper quantiles. A possible reason can be that higher wage earners are often those having greater sense of responsibility to take care of their family and so work much harder to earn their wages, while those high wage earners having married before have a larger incentive to work harder for earning wages as a supplement of love.

From Figure 7 to 12, it is not surprising to find that the quantile estimates of the coefficients of *chiim* in most census and by-census years are negative in sign. The wage differential between natives and Chinese immigrants is larger at higher quantiles. Since natives often know the situation of local labour market and industries better than Chinese immigrants, they may have better working performance and so earn higher wages in skill-intensive industries which may offer higher wages. The familiarity of local workers with the labour market can also favour native workers in their job hunts, but their working performance may not have a great difference with that of Chinese immigrants in labour-intensive industries which treasure physical skills. This enlarges the wage gap between natives and immigrants at upper quantile levels more than that at lower quantiles. Besides, the results in Table 13 to 18 show that the wage gaps between natives and Chinese immigrants increase at the lower and middle quantile levels since 1980s, while that at the upper quantile fluctuates between 10 percent to 30 percent. As mentioned before, the labour-intensive industries may treasure the sense of familiarity of local industries much more and so prefer natives to Chinese immigrants, enlarging the wage gap between natives and Chinese immigrants at lower quantiles over years.

It is not counter-intuitive to find that most of the quantile estimates of age dummies in most census and by-census years are positive in sign, since the base group is the most bottom aged group. In Figure 7 to 12, all the curves of age dummies are positively sloped, suggesting that life experience (or working experience) benefits the high wage earners more than the low wage earners. The curve of *age2635* is positively sloped in 1981, but later grows into an inverted U shape. The curve of *age3645* also has this trend of change starting from 2001. It suggests that small

amount of life experience is increasingly non-beneficial to high wage earners. All estimates of the age dummies at the low quantile level increase over years. Before 2000s, the quantile estimates at the low quantile level of *age4655* and *age5665* are negative, implying that wages decline with high age especially in low wage jobs. The effect increases over years and becomes positive after 2000s. From Table 13 to 18, it can be found that most quantile estimates of the age dummies at different quantile levels increase over years except that of *age2635* at the 90th decile.

The results of the education dummies shown by Figure 7 to 12 provide much detailed information on how different education levels affect the wage levels of different wage earners. In 1980s, the quantile estimates of *f3* and *f5* both constitute positive sloping curves. The curves fluctuate in 1991 and from 1996 onwards, they become negatively sloped in the lower half and fluctuate in the upper half of the distribution. There is a trend for the curves to become negatively sloped over the whole range of the distribution. This implies that the lower education qualifications become increasingly inferior in affecting the wage level of high wage earners compared with that of low wage earners. The situation is similar for the *f7* and postsecondary qualifications, since the quantile estimates of *f7* and *postsec* both constitute positive sloping curves from 1981 to 1991 and later fluctuate at two different range levels for the lower half and upper half of the distribution. For *undergrad* and *postgrad*, the estimates are always uniform over the lower half of the distribution and constitute a deep positive sloping curve over the upper half of the distribution. This implies that high education provide high wage earners with great wage premium over low wage earners with the same education qualification, suggesting that for those who cannot make it to the professional or managerial jobs, having university education does not

mean much at all. In general, there is a trend of increasing inferiority of education proceeding from the lower education to the upper education, which implies the economy increasingly disfavor lower education and there is a demand for higher and higher education of workers. Similar to the trend of mean returns to education, the returns to different education levels at different quantiles generally increase since 1980s, though there is a temporary decrease at the 10th and 90th decile from 1986 to 1991, and decrease from 2001 to 2006. This can be noted from the changes in values of the quantile estimates in Table 13 to 18. A possible explanation is similar to that for mean returns. China's opening up since 1980s gave new opportunities to various Hong Kong industries to grow, which created demand on HK talents and so raised their returns to education. Later the serious skill mismatch problem in the post-Asian Financial Crisis period with the occurrence of various unfavourable events such as SARS hit the economy and decrease the returns to all education groups at various quantiles.

The changing pattern of the quantile estimates of different industry dummies can also be noted from Figure 7 to 12. For *manu*, most quantile estimates are negative in 1981, but in 2006 the estimates in the upper half of the distribution are positive. This suggests that working in the manufacturing sector increasingly provides wage premium over working in the construction sector for high wage earners, since there is skill upgrading in the manufacturing sector. Nevertheless, any low wage earners who continue to work in manufacturing probably are just hanging on to disappearing jobs and so earn much lower wage compared with the construction workers. For *wrtrh*, *tsc*, *finance* and *socser*, the quantile estimate curves have a general pattern of changing from negatively sloped, to inverted U-shape, and then to positively sloped. From

1981 to 2006, the effect of these covariates changes from decreasing from lower to upper quantiles to increasing. Considering the estimates of *manu* in Table 13 to 18, it can be found that the estimates at the lower and middle quantiles generally increase over years. Skill upgrading in the manufacturing sector benefit those wage earners over the lower half of the distribution, though there is still wage disadvantage of manufacturing workers compared with construction workers.

7.2.3 2nd step: Quantile-based Decomposition

After running RIF regressions across quantiles (unconditional quantile regressions) on the wage vector in year 1, the wage vector in year 0 and the counterfactual wage vector, quantile-based decomposition, which resembles the OB decomposition, is performed to decompose changes in wages across quantiles into the wage structure effect and the composition effect. Figure 13 to 17 in the Appendix show the overall change in log wages at each decile and the decomposition of this overall change into the composition effect and the wage structure effect. By comparing the relative log wage changes at different vigintiles, we can know whether there is an increase in wage dispersion with the consideration of the whole distribution. Suppose the changes for all vigintiles are in the same direction, a positive slope of the curve constructed by the quantile estimates implies that the log wage changes at upper vigintiles are larger than those at the lower vigintiles. The wage change for high wage earners is larger than that for low wage earners, contributing to an increase in wage dispersion and vice versa; if the changes are negative at the lower vigintiles and positive at the higher vigintiles, there is an increase in wage dispersion in a way which the wages of high wage earners increase while the wages of low wage earners

decrease. From the four consecutive year pairs since 1980s, the curve of total change is positively sloped, as shown by Figure 13 to 16. Nevertheless, Figure 17 shows that the curve of total change is negatively sloped. This implies there was an increase in wage dispersion among workers from 1980s but a decrease from 2001 to 2006. The situation of wage dispersion from 2001 to 2006 shown by the quantile-based decomposition is opposite to that shown by the summary measures in Table 6 in the Appendix discussed in Chapter 5. For composition effect and wage structure effect, the results are consistent with those of the kernel density estimates in the 1st step. The composition effect and the wage structure effect are always positive and negative respectively. Regarding the composition effect, it always increases the wage dispersion except from 2001 to 2006 as shown by the positive sloping curve in Figure 13 to 17, while the wage structure effect always decreases wage dispersion before mid-1990s. It does not have obvious effect on wage dispersion from 1996 to 2001, but it increases wage dispersion from 2001 to 2006. The shape of the curve of total change generally follows that of the composition effect, suggesting that the composition effect dominates the changes in wage dispersion rather than the wage structure effect. Clues on the underlying reasons contributing to these results can be found from the estimates of each variable. The decomposition results are also presented in table and graphical forms. The tables including Table 19 to 23 in the Appendix can provide a quick glance and easy comparison of all effects of covariates at the chosen deciles in each year pair, while the graphical displays including Figure 18 to 22 in the Appendix can provide a more detailed picture of the covariate effect across vigintiles compared with the utilization of tables, since more estimates at different quantiles can be shown in a concise manner. Comparison on the relative strengths of the covariate effects can also be made easily.

Regarding gender, the male status generally increases the dispersion of the whole wage distribution over the years. The composition effect is generally negative and the curve is positively sloped over years, but it becomes flatter and flatter. Besides, the magnitude of composition effect increases at the lower, the middle and the upper deciles over years, as shown by the results in the tables. This suggests that the percentage of male workers decreases over the whole range of the distribution. The wage structure effect is always positive and the curve is originally positively sloped from 1981 to 1986, but starting from the 1990s it becomes flat⁷¹. Since the gender wage gaps at the lower and the middle decile levels have narrowed over the years, as mentioned in the previous section, gender has a decreasing wage structure effect on increasing the wage dispersion over the whole distribution. The gender wage gap over the whole distribution increases at a decreasing rate mainly due to the composition effect.

The total effect of *chiim* on changes in wage dispersion has a change over years. The curve of the total change is positively sloped at the upper half of the distribution since 1980s but becomes flatter and flatter and is later negatively sloped from 2001 to 2006. This suggests that the status of *chiim* originally increases wage dispersion of the whole distribution in 1980s but later has a wage dispersion decreasing effect over the whole range of the distribution from 2001 to 2006. The composition effect is generally positive and the curve is positively sloped over years, but it becomes flatter and flatter and is later negatively sloped from 2001 to 2006. Besides, the magnitude of composition effect decreases at the lower, the middle and the upper deciles, as

⁷¹ The curve is flat if the extreme case at the lowest vigintile (i.e. the 5th vigintile) is neglected.

shown by the results in the tables. This suggests that the percentage of Chinese immigrant workers decreases over the whole range of the distribution. The wage structure effect is always negative and the curve is originally negatively sloped from 1981 to 1986, but starting from mid-1990s it becomes flat. Since the wage gap between natives and the Chinese immigrants at the upper decile (90th decile) decreases faster over years than those at the other deciles, the wage structure effect of *chiim* on decreasing the wage dispersion over the whole distribution vanishes. Similar to gender, the composition effect plays a larger role than the wage structure effect in shaping the total effect of *chiim*.

Regarding the effect of age dummies, all age dummies increase the wage dispersion of the whole distribution but later decrease the wage dispersion from 2001 to 2006, as shown by the gradual change of slope of the curve from positive to negative. The composition effect is always positive for all age dummies in all year pairs except for *age2635* and *age3645* from 2001 to 2006. The log wage changes contributed by these two dummies at some vigintiles over the upper half of the distribution are negative. The values of the composition effect of these two dummies at the lower, the middle and the upper deciles decrease over years, as shown by the tables. The wage structure effect is always negative for all age dummies in all year pairs except for *age2635* over the upper half of the distribution from 2001 to 2006. The curves for the age dummies except *age2635* are generally negatively sloped in the 1980s, become flat in the 1990s and then become positively sloped in the 2000s. The curve of the wage structure effect of *age2635* has a weak U-shaped pattern in the 1980s and later has positively slope starting from 1990s, suggesting that the wage structure effect of *age2635* has a wage-dispersion-enhancing effect much earlier than other age

dummies. Comparing the relative strength of the composition effect and the wage structure effect, the composition effect plays a larger role than the wage structure effect in affecting the changes in wage dispersion.

The total effect of the education dummies on the changes in wage dispersion over years is similar to that of the age dummies. All education dummies increase the wage dispersion of the whole distribution but later decrease the wage dispersion from 2001 to 2006, as shown by the gradual change of slope of the curve from positive to negative. The composition effect is always positive for all education dummies at all vigintiles. The curves for the dummies of F5 or above change from positively sloped in 1980s to negatively sloped in 2000s except *postgrad*. The curve of the composition effect of *postgrad* is flat from 2001 to 2006. The curves of the composition effect of *f3* exhibit similar pattern of change, but the change starts from early 1990s. These results imply that the wage dispersion decreasing manner of the composition effect started at the lower education level earlier and later progressed to the higher education level. The wage structure effect for all education dummies at all vigintiles is roughly symmetrical with the composition effect. Again, the composition effect plays a larger role than the wage structure effect in shaping the total effect of the education dummies except the case of *postgrad* from 2001 to 2006.

The effects of different industry dummies on changes in wage dispersion show different patterns. Similar to the part on interpreting the results of industry dummies in OB decomposition, only the effects of *manu* and *finance* are discussed here. Regarding *manu*, the curve of total effect changes from positively sloped in 1980s to negatively sloped in 2000s, implying it increases the wage dispersion over the whole

distribution but later its effect reverses. The composition effect is originally negative, but later it becomes positive and has a negatively sloping curve. The slope of the curve becomes less steep in 2000s. The wage structure effect is firstly positive, then becomes negative and has positively sloping curve in 1990s but the curve becomes inverted U-shaped in 2000s. This implies there is a polarization of wages between the manufacturing and the construction. Later the changes in wage differential are roughly uniform across the whole distribution. Regarding *finance*, it always increases the wage dispersion of the whole distribution. The curve of the composition effect is originally positively sloped and later becomes negatively sloped, while the curve of the wage structure effect is originally negatively sloped, becomes flatter and later becomes positively sloped. This implies that the composition effect shapes the effect of *finance* on increasing the wage dispersion but later the wage structure effect takes up the role. Both *manu* and *finance* increase the wage dispersion of the whole distribution in 1980s, but later the effect of *manu* diminishes and counteracts the effect of *finance*.

To sum up briefly, the factors of age and education are the major force in driving the changes in wage dispersion, since the trend of the change follows closely with the effect of these two factors. Gender and the financial sector always have an effect of increasing the wage dispersion over the whole distribution. A summary and more detailed discussion on the implication of the results will be made in the last chapter.

Chapter 8

Summary and Conclusion

The issue of wage dispersion has been a major concern in Hong Kong. There have been lots of studies exploring the underlying reasons of the changes in wage dispersion over the time. This thesis makes contributions to the study of Hong Kong wage dispersion since 1980s by using alternative methods which focus on the changes in the entire wage distribution instead of relying on the calculation of summary measures or other common approaches. Also, it is amongst the few updated studies which attempt to investigate the situation of wage dispersion since 2000s. Due to its advantages mentioned in previous chapters, the FFL approach, one of the novel methods in an approach called distributional approach, is chosen as the core methodology in studying the issue concerned. The traditional OB decomposition is also carried out and the results provide a preliminary overview of changes in wage dispersion.

As discussed in Chapter 5, most of the summary measures have increasing values since 1980s⁷², implying that there is a continuous increase in wage dispersion. This supports many findings of previous studies such as Chau (1984), Li (2006) and Lui (1997). Nevertheless, many of those studies investigated the changes in Hong Kong wage dispersion before 2000s. Lui (2008) is amongst the few updated studies which includes the exploration of the situation of wage dispersion after 2000s. By referring to the decile ratios, he found that there is widening wage dispersion among the high wage earners, but there is a narrowing of the wage dispersion among low wage

⁷² Please refer to Table 6 in the Appendix for the details.

earners. This result matches the calculation result of quantile ratios in Table 6. Nevertheless, because of the inadequacies discussed before, the results of these summary measures may not be able to provide a comprehensive picture on the changes in wage dispersion and are sometimes misleading. For example, in Table 6, the coefficient of variation decreases in value from 1991 to 1996, showing a decrease in wage dispersion. In contrast, other summary measures increase in value, which implies there is an increase in wage dispersion. Regarding the results of FFL approach, the decomposition results also reveal that there was an increase in wage dispersion over the whole distribution in the last two decades before 2000s, but a decrease from 2001 to 2006. This is different from the results of Lui (2008) and what is indicated by quantile ratios in Table 6, which only reveal a decrease in wage dispersion in the lower half of the distribution. The results of FFL approach should be more convincing, since it puts equal weights to every point over the whole range of the distribution. The results of OB decomposition show a continuous increase in the mean wage since 1980s but a decrease from 2001 to 2006. The year 2000 seems to be a hallmark of the change in Hong Kong wage dispersion situation.

The possible reasons for the increase in wage dispersion since 1980s such as economic restructuring, trade or immigration have been widely explored in many studies. Considering the quantile-based decomposition results of FFL approach in this thesis, it is found that the composition effect dominates the wage structure effect. Changes in the distribution of labour market characteristics among the labour force are more important in shaping the dynamics of wage dispersion than changes in returns to the characteristics. Interestingly, the composition effect and the wage structure effect often work in the opposite direction. When the composition effect

becomes more positive at upper vigintiles, the wage structure effect becomes more negative. This implies that the changes in the distribution of characteristics and the returns to these characteristics are highly responsive to each other, suggesting that our labour market is highly responsive to structural changes. It is not surprising to find that the factors of age and education are the major forces in affecting the changes in wage dispersion, since they are significant factors in affecting the levels of labour income and thus the wage dispersion among workers. The increase in the proportion of female, the proportion of natives and the general education levels have contributed to the increase in wage dispersion in 1980s and 1990s. Besides, the skill-upgrading in the manufacturing sector and the development of the financial sector also play a role. In the post-Asian financial Crisis period starting from 2000s, the economy experienced various unfavourable events such as SARs which hit the economy seriously. The decrease in wage dispersion from 2001 to 2006 can be due to the oversupply of high educated workers, which leads to a decrease in returns and so the wages of high educated workers. Moreover, the general skill-upgrading in labour-intensive industries also raise the wages of low wage earners, which narrows the wage dispersion over the whole wage distribution. In brief, the development of the economy since 1980s increased the wage dispersion. Nevertheless, the oversupply of high educated workers and general skill-upgrading in labour-intensive industries decreased the wage dispersion since 2000s. With the larger and larger proportion of high educated workers in the labour market and general wage improvement of low wage workers due to other reasons such as the implementation of minimum wage, wage dispersion in Hong Kong may continue to decrease in the near future.

Furthermore, referring to the results of RIF regressions across the quantiles in the previous chapter, the coefficient estimates at the higher deciles are generally more statistically significant than those at the lower deciles. In addition, the values of the adjusted $R\text{-bar}^2$ are higher at the higher deciles. The model specification in this thesis can explain the wage structure at the upper deciles better than at the lower deciles. The common wage-determining factors may not be able to explain the earnings-profile of low wage earners well. It could be that at the low end, there is more diversity in the quality of the workers beyond the general descriptions offered by the variables. For instance, physical strength may affect the wage levels of low wage earners in construction sector more than education does. Besides, location factors may play a role. There may also be more "local markets" such that some workers are trapped in the locality given high transportation costs and have to accept very low wages.

There is a policy implication for the government regarding education. As mentioned in the previous chapter, the increase in the supply of workers with postsecondary education or above was larger than the increase in the respective demand. Thus the government may need to consider whether it is worthwhile to continuously increase the proportion of highly educated workers especially in this period of post-worldwide financial turmoil. Lastly, there are certain problems in this study. First, there can be a missing variable problem. For example, the quality of schooling and hours of work cannot be controlled; second, returns to education may be overestimated since in-school experience is ignored (Light, 2001). These problems often arise due to data limitation and may be solved depending on the quality of the data used.

Appendix

Chart 1: Composite CPI from 1981 to 2008 (1981=100)

Data source: Hong Kong Census and Statistics Department

Table 1 Number of records in all 6 census years

	1981 (1%)	1986 (1%)	1991 (5%)	1996 (5%)	2001 (1%)	2006 (1%)
All records	60339	74189	352589	402930	89860	92215
Quarter records	10336	16926	75485	89092	20152	22261
Household records	12222	18328	79985	93051	22046	23534
Person records (Cases eligible for use)	48117 (18166)	55861 (20631)	272604 (102654)	313838 (118282)	69708 (25175)	69954 (26234)

Table 2 Classification of occupations

<i>priwork</i>	Skilled agricultural and fishery workers, labourers in mining, construction, manufacturing, agriculture and fishing
<i>manager</i>	Managers and administrators
<i>pro</i>	Professionals and associate professionals
<i>clerk</i>	Clerks
<i>service</i>	Service workers and shop sales workers, sales and services elementary occupations
<i>secworker</i>	Craft and related workers, plant and machine operators and assemblers

* The classification here is based on the information of series60 OCCUP in 2006 population by-census dataset userguide.

Table 3: Variable meanings

Variables	Meanings
<i>lnrwage</i>	Natural logarithm of real wage
<i>male</i>	Gender dummy with male = 1, all else = 0
<i>nomarr</i>	Marital-status dummy with people never get married before = 1, all else = 0
<i>spouse</i>	Marital-status dummy with people married with spouse = 1, all else = 0
<i>marrbef</i>	Marital-status dummy with people being divorced or widowed = 1, all else = 0
<i>native</i>	Place-of-origin dummy with Hong Kong natives = 1, all else = 0
<i>chiim</i>	Place-of-origin dummy with Chinese immigrants = 1, all else = 0
<i>overseaim</i>	Place-of-origin dummy with oversea immigrants = 1, all else = 0
<i>exp</i>	Potential work experience (defined as $age - age1525$)
<i>age1525</i>	Age dummy with people aged 15-25 = 1, all else = 0
<i>age2635</i>	Age dummy with people aged 26-35 = 1, all else = 0
<i>age3645</i>	Age dummy with people aged 36-45 = 1, all else = 0
<i>age4655</i>	Age dummy with people aged 46-55 = 1, all else = 0
<i>age5665</i>	Age dummy with people aged 56-65 = 1, all else = 0
<i>pri</i>	Educational dummy with people having primary school qualification or below = 1, all else = 0
<i>f3</i>	Educational dummy with people having Form 3 qualification = 1, all else = 0
<i>f5</i>	Educational dummy with people having Form 5 qualification = 1, all else = 0
<i>f7</i>	Educational dummy with people having Form 7 qualification = 1, all else = 0
<i>postsec</i>	Educational dummy with people having postsecondary qualification = 1, all else = 0

<i>undergrad</i>	Educational dummy with people having undergraduate qualification = 1, all else = 0
<i>postgrad</i>	Educational dummy with people having postgraduate qualification = 1, all else = 0
<i>priin</i>	Industry dummy with workers in primary sector = 1, all else = 0
<i>manu</i>	Industry dummy with workers in manufacturing sector = 1, all else = 0
<i>egw</i>	Industry dummy with workers in sector of electricity, gas and water = 1, all else = 0
<i>cons</i>	Industry dummy with workers in construction sector = 1, all else = 0
<i>wrtrh</i>	Industry dummy with workers in sector of wholesale, retail and import/export trades, restaurants and hotels = 1, all else = 0
<i>tsc</i>	Industry dummy with workers in sector of transport, storage and communication = 1, all else = 0
<i>finance</i>	Industry dummy with workers in sector of financing, insurance, real estate and business services = 1, all else = 0
<i>socser</i>	Industry dummy with workers in sector of community, social and personal services = 1, all else = 0
<i>priwork</i>	Occupation dummy with workers as primary workers = 1, all else = 0
<i>manager</i>	Occupation dummy with workers as managers = 1, all else = 0
<i>pro</i>	Occupation dummy with workers as professionals = 1, all else = 0
<i>clerk</i>	Occupation dummy with workers as clerks = 1, all else = 0
<i>service</i>	Occupation dummy with workers as service workers = 1, all else = 0
<i>secworker</i>	Occupation dummy with workers as secondary workers = 1, all else = 0

**agelfsh*: age left school

Table 4 Age left school (*agelfsh*) corresponding to the appropriate year of obtaining the highest level of educational qualification

Age left school (<i>agelfsh</i>)	Corresponding educational qualifications
15	No schooling, kindergarten, primary school (Grade 1 to Grade 6), Form 1 (Grade 7) to Form 3 (grade 9)
16	Form 4 (Grade 10)
17	Form 5 (Grade 11), craft level
18	Form 6 (Grade 12) and Project Yi Jin
19	Form 7 (Grade 12), certificate/ diploma courses, nurse training courses, dental training courses, distance learning courses
21	Higher certificate/ diploma courses, associate degrees, sub-degree level nurse training courses, sub-degree level dental training courses, sub-degree level distance learning courses
22	First degree courses
23	Postgraduate certificate/ diploma courses, master degree courses
24	Master of Philosophy (MPhil) courses
27	Doctor of Philosophy (PhD) courses

* The classification here is based on the information of series52 EDUCNH in 2006 population by-census dataset userguide.

Table 5a: Descriptive statistics of sample characteristics from 1981 to 1991

	1981	1986	1991
	Mean (SD)		
Age	33.11 (12.52)	33.90 (11.77)	35.08 (11.29)
(Potential) working experience	17.16 (12.76)	17.56 (12.16)	18.46 (11.82)
	Percentage		
Gender			
Male	62.74	61.02	60.07
Marital status			
Never get married	45.05	42.44	39.51
Having a spouse	52.30	54.83	57.98
Married before	2.66	2.73	2.51
Place of origin			
Native	49.55	56.61	59.51
Chinese immigrants	46.63	39.12	34.06
Oversea immigrants	3.82	4.27	6.43
Age groups			
Aged from 15-25	36.57	29.36	21.68
Aged from 26-35	27.97	33.75	36.39
Aged from 36-45	14.95	17.21	23.14
Aged from 46-55	13.83	13.09	11.92
Aged from 56-65	6.68	6.58	6.86
Education			
Primary education	45.74	34.62	26.62
F3	20.21	20.44	21.21
F5	23.23	28.63	32.34
F7	3.69	4.94	5.94
Postsecondary	3.47	6.00	6.96
Undergraduate	3.28	4.89	6.35
Postgraduate	0.38	0.48	0.59
Industry			
Primary	0.65	0.61	0.41
Manufacturing	43.99	39.16	28.66
Electricity, gas and water	0.73	0.95	0.76
Construction	9.01	6.76	6.99
Wholesale, retail and import/export trades, restaurants and hotels	15.25	18.50	20.54
Transport, storage and	7.76	7.74	9.88

communication			
Financing, insurance, real estate and business services	5.43	6.81	11.24
Community, social and personal services	16.13	19.14	21.22
Occupation			
Primary workers	0.72	0.65	4.76
Managers	1.76	2.50	4.70
Professionals	6.01	8.80	15.38
Clerks	14.34	16.50	18.15
Service workers	21.96	24.21	27.14
Secondary workers	54.53	43.32	29.48
N	19013	21686	110172

*SD: standard deviation

Table 5b: Descriptive statistics of sample characteristics from 1996 to 2006

	1996	2001	2006
	Mean (SD)		
Age	36.13 (10.61)	37.26 (10.61)	38.24 (10.79)
(Potential) working experience	18.98 (11.34)	19.84 (11.43)	20.58 (11.71)
	Percentage		
Gender			
Male	57.57	52.90	51.11
Marital status			
Never get married	36.56	36.54	37.61
Having a spouse	60.39	59.69	57.69
Married before	3.06	3.77	4.70
Place of origin			
Native	61.25	62.84	65.72
Chinese immigrants	29.88	27.15	24.74
Oversea immigrants	8.86	10.00	9.54
Age groups			
Aged from 15-25	17.24	15.58	14.36
Aged from 26-35	35.17	30.31	28.28
Aged from 36-45	27.74	30.52	29.39
Aged from 46-55	14.04	18.49	21.93
Aged from 56-65	5.81	5.10	6.04
Education			
Primary education	19.74	16.94	13.43
F3	20.45	19.42	19.38
F5	33.04	31.45	32.02
F7	7.54	9.71	8.72
Postsecondary	6.22	6.97	8.32
Undergraduate	10.97	12.88	14.34
Postgraduate	2.05	2.63	3.96
Industry			
Primary	0.21	0.16	0.11
Manufacturing	18.78	11.81	9.38
Electricity, gas and water	0.74	0.61	0.48
Construction	8.52	7.55	7.03
Wholesale, retail and import/export trades, restaurants and hotels	22.69	24.82	25.55
Transport, storage and	10.88	10.77	11.16

communication			
Financing, insurance, real estate and business services	14.12	16.87	17.57
Community, social and personal services	23.86	27.36	28.61
Occupation			
Primary workers	2.90	2.62	1.96
Managers	7.60	7.46	6.80
Professionals	18.47	22.03	23.12
Clerks	18.77	17.93	18.21
Service workers	30.34	33.84	35.39
Secondary workers	21.70	16.10	14.42
N	130074	28021	29034

*SD: standard deviation

Table 6: Description of central tendency and dispersion of wages in all 6 census years

	1981	1986	1991	1996	2001	2006
Nominal mean	\$1734	\$3238	\$6942	\$13027	\$15636	\$14756
(SD)	(\$1409)	(\$2870)	(\$6613)	(\$13317)	(\$15850)	(\$15136)
Real mean	1734	2276	3168	3956	4793	4669
(SD)	(1409)	(2017)	(3018)	(4044)	(4858)	(4789)
Relative mean deviation	0.228	0.250	0.257	0.279	0.300	0.305
Coefficient of variation	0.813	0.886	0.953	1.022	1.014	1.026
Gini coefficient	0.324	0.354	0.361	0.389	0.413	0.420
Theil entropy measure	0.205	0.244	0.264	0.303	0.324	0.332
10th decile	800	914	1369	1518	1625	1582
50th decile (median)	1450	1757	2373	2885	3372	3164
90th decile						
P90/P10	3000	3866	5659	6832	9196	9097
P90/P50						
	3.75	4.23	4.13	4.50	5.66	5.75
P50/P10						
	2.07	2.20	2.38	2.37	2.73	2.88
	1.81	1.92	1.73	1.90	2.08	2
N	18166	20631	102654	118282	25175	26234

*The mean and standard deviation are at current prices

Table 7: OLS estimates of Mincerian wage models (mean estimates) for all census and by-census years

	(1) 1981	(2) 1986	(3) 1991	(4) 1996	(5) 2001	(6) 2006
<i>male</i>	0.351*** (43.75)	0.303*** (41.02)	0.280*** (86.61)	0.222*** (68.72)	0.256*** (35.48)	0.179*** (23.47)
<i>spouse</i>	0.133*** (13.26)	0.167*** (18.06)	0.174*** (43.78)	0.152*** (38.16)	0.163*** (17.82)	0.187*** (19.35)
<i>marrbef</i>	0.0294 (1.17)	0.104*** (4.47)	0.101*** (9.79)	0.108*** (11.35)	0.0938*** (4.80)	0.0982*** (5.16)
<i>chiim</i>	-0.0832*** (-9.66)	-0.135*** (-16.15)	-0.152*** (-41.50)	-0.175*** (-48.96)	-0.187*** (-22.92)	-0.243*** (-28.08)
<i>age2635</i>	0.198*** (18.56)	0.238*** (24.24)	0.218*** (48.92)	0.214*** (44.87)	0.348*** (30.55)	0.402*** (32.26)
<i>age3645</i>	0.137*** (9.49)	0.275*** (20.56)	0.289*** (51.65)	0.310*** (55.61)	0.479*** (37.77)	0.552*** (40.41)
<i>age4655</i>	0.0681*** (4.47)	0.205*** (13.66)	0.179*** (26.20)	0.254*** (38.50)	0.470*** (32.54)	0.528*** (35.06)
<i>age5665</i>	-0.0615*** (-3.32)	0.0481** (2.65)	0.0240** (3.01)	0.0694*** (8.28)	0.277*** (13.92)	0.445*** (22.30)
<i>f3</i>	0.103*** (10.17)	0.151*** (14.97)	0.161*** (35.47)	0.165*** (33.96)	0.207*** (18.10)	0.162*** (12.42)
<i>f5</i>	0.285*** (28.18)	0.339*** (35.25)	0.407*** (91.96)	0.457*** (96.66)	0.531*** (47.45)	0.464*** (36.78)
<i>f7</i>	0.383*** (18.38)	0.471*** (26.78)	0.608*** (83.21)	0.662*** (96.22)	0.676*** (44.14)	0.554*** (32.28)
<i>postsec</i>	0.686*** (32.61)	0.752*** (47.27)	0.799*** (118.80)	0.867*** (119.88)	0.968*** (61.19)	0.799*** (48.53)
<i>undergrad</i>	0.873*** (38.40)	1.000*** (54.37)	1.096*** (147.14)	1.080*** (169.43)	1.217*** (86.36)	1.090*** (72.11)
<i>postgrad</i>	1.263*** (19.26)	1.393*** (25.38)	1.443*** (68.65)	1.436*** (120.80)	1.570*** (67.20)	1.351*** (63.35)
<i>manu</i>	-0.221*** (-17.05)	-0.0844*** (-6.02)	-0.0746*** (-12.08)	-0.0450*** (-7.40)	-0.0349* (-2.27)	0.0494** (2.83)
<i>egw</i>	-0.0228 (-0.52)	0.168*** (4.54)	0.152*** (8.64)	0.152*** (8.61)	0.243*** (5.61)	0.272*** (5.31)
<i>wrtrh</i>	-0.0678*** (-4.59)	0.0823*** (5.46)	0.0488*** (7.58)	-0.00525 (-0.88)	-0.0723*** (-5.20)	-0.00720 (-0.48)
<i>tsc</i>	0.00402 (0.23)	0.123*** (7.01)	0.0303*** (4.21)	0.0203** (3.04)	-0.0290 (-1.86)	0.0162 (0.97)
<i>finance</i>	-0.0182 (-0.90)	0.183*** (9.73)	0.117*** (16.06)	0.0958*** (14.50)	0.0391** (2.60)	0.110*** (6.85)
<i>socser</i>	0.0350* (2.31)	0.229*** (14.79)	0.124*** (18.64)	0.136*** (21.79)	0.0934*** (6.44)	0.0613*** (3.95)
<i>constant</i>	6.895*** (455.41)	6.843*** (410.96)	7.102*** (935.83)	7.204*** (945.92)	7.118*** (393.81)	7.040*** (343.68)
<i>N</i>	18166	20631	102654	118282	25175	26234
<i>adj. R²</i>	0.350	0.401	0.408	0.397	0.446	0.388

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Conventional Oaxaca-Blinder decomposition (mean decomposition) of changes in wage dispersion from 1981 to 1986

Prediction for 1986: 7.514 ^{***} (1710.74) Prediction for 1981: 7.271 ^{***} (1621.74) Overall changes: 0.243 ^{***} (38.67)		
	Composition Effect	Wage Structure Effect
<i>male</i>	-0.00454 ^{**} (-2.62)	-0.0291 ^{***} (-4.34)
<i>spouse</i>	0.00380 ^{***} (5.17)	0.0187 [*] (2.52)
<i>marrbef</i>	0.0000141 (0.28)	0.00200 [*] (2.17)
<i>chiim</i>	0.00635 ^{***} (8.14)	-0.0213 ^{***} (-4.33)
<i>age2635</i>	0.0118 ^{***} (10.52)	0.0138 ^{**} (2.82)
<i>age3645</i>	0.00322 ^{***} (5.29)	0.0230 ^{***} (6.95)
<i>age4655</i>	-0.000568 [*] (-2.12)	0.0178 ^{***} (6.37)
<i>age5665</i>	0.0000611 (0.39)	0.00730 ^{***} (4.20)
<i>f3</i>	0.000445 (1.05)	0.0101 ^{***} (3.37)
<i>f5</i>	0.0158 ^{***} (11.42)	0.0155 ^{***} (3.86)
<i>f7</i>	0.00458 ^{***} (5.64)	0.00416 ^{**} (3.21)
<i>postsec</i>	0.0182 ^{***} (11.63)	0.00395 [*] (2.48)
<i>undergrad</i>	0.0111 ^{***} (6.79)	0.00515 ^{***} (4.30)
<i>postgrad</i>	0.00107 (1.40)	0.000511 (1.50)
<i>manu</i>	0.0105 ^{***} (8.26)	0.0544 ^{***} (7.12)
<i>egw</i>	-0.0000531 (-0.51)	0.00183 ^{**} (3.23)
<i>wrtrh</i>	-0.00235 ^{***} (-4.09)	0.0285 ^{***} (7.07)
<i>tsc</i>	0.00000266 (0.17)	0.00944 ^{***} (4.80)
<i>finance</i>	-0.000274 (-0.89)	0.0138 ^{***} (7.15)
<i>socser</i>	0.000854 [*] (2.18)	0.0351 ^{***} (8.89)
<i>constant</i>		-0.0518 [*] (-2.30)
Total	0.0799 ^{***} (20.19)	0.163 ^{***} (31.29)

t statistics in parentheses

^{*} $p < 0.05$, ^{**} $p < 0.01$, ^{***} $p < 0.001$

Table 9: Conventional Oaxaca-Blinder decomposition (mean decomposition) of changes in wage dispersion from 1986 to 1991

Prediction for 1991: 7.839 ^{***} (4052.27) Prediction for 1986: 7.514 ^{***} (1710.74) Overall changes: 0.325 ^{***} (67.64)		
	Composition Effect	Wage Structure Effect
<i>male</i>	-0.000485 (-0.43)	-0.0141 ^{**} (-2.85)
<i>spouse</i>	0.00564 ^{***} (7.97)	0.00360 (0.62)
<i>marrbef</i>	-0.000224 (-1.64)	-0.0000589 (-0.09)
<i>chiim</i>	0.00613 ^{***} (9.70)	-0.00630 (-1.89)
<i>age2635</i>	0.00612 ^{***} (6.81)	-0.00747 (-1.91)
<i>age3645</i>	0.0168 ^{***} (14.67)	0.00309 (0.93)
<i>age4655</i>	-0.00283 ^{***} (-5.04)	-0.00305 (-1.59)
<i>age5665</i>	0.000175 (1.54)	-0.00169 (-1.22)
<i>f3</i>	0.00156 ^{**} (3.25)	0.00223 (0.92)
<i>f5</i>	0.0126 ^{***} (10.27)	0.0219 ^{***} (6.38)
<i>f7</i>	0.00371 ^{***} (4.72)	0.00758 ^{***} (7.17)
<i>postsec</i>	0.00735 ^{***} (5.29)	0.00334 ^{**} (2.76)
<i>undergrad</i>	0.0111 ^{***} (7.19)	0.00493 ^{***} (4.80)
<i>postgrad</i>	0.00176 [*] (2.57)	0.000256 (0.84)
<i>manu</i>	0.00874 ^{***} (5.89)	0.00291 (0.64)
<i>egw</i>	-0.000278 [*] (-2.01)	-0.000129 (-0.40)
<i>wrtrh</i>	0.00198 ^{***} (4.50)	-0.00715 [*] (-2.04)
<i>tsc</i>	0.00289 ^{***} (5.93)	-0.00955 ^{***} (-4.89)
<i>finance</i>	0.00839 ^{***} (8.94)	-0.00755 ^{**} (-3.27)
<i>socser</i>	0.00193 ^{**} (2.81)	-0.0198 ^{***} (-6.21)
<i>constant</i>		0.259 ^{***} (14.13)
Total	0.0931 ^{***} (27.83)	0.232 ^{***} (58.33)

t statistics in parentheses

^{*} $p < 0.05$, ^{**} $p < 0.01$, ^{***} $p < 0.001$

Table 10: Conventional Oaxaca-Blinder decomposition (mean decomposition) of changes in wage dispersion from 1991 to 1996

Prediction for 1996: 8.027 ^{**} (4161.09) Prediction for 1991: 7.839 ^{***} (4052.27) Overall changes: 0.189 ^{***} (69.07)		
	Composition Effect	Wage Structure Effect
<i>male</i>	-0.00319 ^{***} (-5.45)	-0.0349 ^{***} (-12.67)
<i>spouse</i>	0.00509 ^{***} (13.31)	-0.0131 ^{***} (-3.84)
<i>marrbef</i>	0.000523 ^{***} (5.93)	0.000194 (0.46)
<i>chiim</i>	0.00552 ^{***} (16.40)	-0.00726 ^{***} (-4.33)
<i>age2635</i>	-0.00397 ^{***} (-8.78)	-0.00129 (-0.57)
<i>age3645</i>	0.0146 ^{***} (24.22)	0.00598 ^{**} (2.72)
<i>age4655</i>	0.00449 ^{***} (14.65)	0.0107 ^{***} (7.94)
<i>age5665</i>	-0.000254 ^{**} (-2.88)	0.00271 ^{***} (3.92)
<i>f3</i>	-0.000769 ^{**} (-2.71)	0.000876 (0.61)
<i>f5</i>	0.00495 ^{***} (6.06)	0.0169 ^{***} (7.74)
<i>f7</i>	0.00907 ^{***} (14.27)	0.00379 ^{***} (5.37)
<i>postsec</i>	-0.00559 ^{***} (-6.56)	0.00423 ^{***} (6.78)
<i>undergrad</i>	0.0454 ^{***} (36.76)	-0.00143 (-1.57)
<i>postgrad</i>	0.0187 ^{***} (26.64)	-0.000125 (-0.29)
<i>manu</i>	0.00729 ^{***} (11.78)	0.00589 ^{***} (3.42)
<i>egw</i>	-0.0000106 (-0.18)	-0.00000215 (-0.01)
<i>wrtrh</i>	0.00129 ^{***} (6.75)	-0.0130 ^{***} (-6.16)
<i>tsc</i>	0.000370 ^{***} (3.83)	-0.00114 (-1.01)
<i>finance</i>	0.00362 ^{***} (12.91)	-0.00309 [*] (-2.16)
<i>socser</i>	0.00143 ^{***} (6.42)	0.00234 (1.28)
<i>constant</i>		0.102 ^{***} (9.48)
Total	0.109 ^{***} (58.35)	0.0801 ^{***} (36.16)

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Conventional Oaxaca-Blinder decomposition (mean decomposition) of changes in wage dispersion from 1996 to 2001

Prediction for 2001: 8.187*** (1808.55) Prediction for 1996: 8.027*** (4161.09) Overall changes: 0.160*** (32.50)		
	Composition Effect	Wage Structure Effect
<i>male</i>	-0.00874*** (-11.28)	0.0188*** (4.24)
<i>spouse</i>	-0.000777 (-1.50)	0.00627 (1.05)
<i>marrbef</i>	0.000763*** (4.94)	-0.000518 (-0.65)
<i>chiim</i>	0.00459*** (8.10)	-0.00363 (-1.36)
<i>age2635</i>	-0.0110*** (-15.20)	0.0392*** (10.76)
<i>age3645</i>	0.00986*** (9.80)	0.0523*** (12.09)
<i>age4655</i>	0.0129*** (17.01)	0.0413*** (13.35)
<i>age5665</i>	-0.000609*** (-4.68)	0.0106*** (9.30)
<i>f3</i>	-0.00212*** (-4.54)	0.00837*** (3.34)
<i>f5</i>	-0.00361* (-2.42)	0.0242*** (6.07)
<i>f7</i>	0.00476*** (3.91)	0.00105 (0.81)
<i>postsec</i>	0.00907*** (5.84)	0.00744*** (5.78)
<i>undergrad</i>	0.0274*** (11.47)	0.0161*** (8.71)
<i>postgrad</i>	0.0106*** (6.91)	0.00342*** (5.01)
<i>manu</i>	0.00323*** (7.18)	0.00127 (0.61)
<i>egw</i>	-0.000195* (-2.18)	0.000602 (1.93)
<i>wrtrh</i>	-0.000141 (-0.88)	-0.0179*** (-4.42)
<i>tsc</i>	0.0000194 (0.43)	-0.00571** (-2.90)
<i>finance</i>	0.00304*** (9.31)	-0.0100*** (-3.45)
<i>socser</i>	0.00323*** (7.73)	-0.00951** (-2.68)
<i>constant</i>		-0.0861*** (-4.39)
Total	0.0623*** (20.57)	0.0976*** (25.97)

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Conventional Oaxaca-Blinder decomposition (mean decomposition) of changes in wage dispersion from 2001 to 2006

Prediction for 2006: 8.149 ^{***} (1781.50) Prediction for 2001: 8.187 ^{***} (1808.55) Overall changes: -0.0382 ^{***} (-5.93)		
	Composition Effect	Wage Structure Effect
<i>male</i>	-0.00424 ^{***} (-3.76)	-0.0422 ^{***} (-7.36)
<i>spouse</i>	-0.00367 ^{***} (-5.00)	0.0143 (1.86)
<i>marrbef</i>	0.000904 ^{***} (3.61)	0.000207 (0.16)
<i>chiim</i>	0.00525 ^{***} (6.73)	-0.0154 ^{***} (-4.72)
<i>age2635</i>	-0.00824 ^{***} (-5.86)	0.0146 ^{**} (3.20)
<i>age3645</i>	-0.00719 ^{***} (-3.68)	0.0218 ^{***} (3.95)
<i>age4655</i>	0.0171 ^{***} (9.70)	0.0134 ^{**} (2.81)
<i>age5665</i>	0.00329 ^{***} (5.37)	0.0105 ^{***} (5.89)
<i>f3</i>	-0.00127 (-1.74)	-0.00877 ^{**} (-2.59)
<i>f5</i>	0.00156 (0.71)	-0.0220 ^{***} (-3.94)
<i>f7</i>	-0.00196 (-1.24)	-0.00909 ^{***} (-5.27)
<i>postsec</i>	0.0130 ^{***} (5.59)	-0.0147 ^{***} (-7.33)
<i>undergrad</i>	0.0266 ^{***} (7.38)	-0.0177 ^{***} (-6.08)
<i>postgrad</i>	0.0227 ^{***} (9.16)	-0.00875 ^{***} (-6.77)
<i>manu</i>	0.000899 [*] (2.21)	0.00851 ^{***} (3.62)
<i>egw</i>	-0.000324 (-1.86)	0.000151 (0.43)
<i>wrtrh</i>	-0.000464 (-1.56)	0.0178 ^{**} (3.17)
<i>tsc</i>	-0.000102 (-1.03)	0.00538 [*] (1.97)
<i>finance</i>	0.000373 (1.91)	0.0132 ^{**} (3.21)
<i>socser</i>	0.00121 ^{**} (3.07)	-0.00763 (-1.51)
<i>constant</i>		-0.0773 ^{**} (-2.83)
Total	0.0655 ^{***} (14.83)	-0.104 ^{***} (-20.59)

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: 1981 unconditional quantile regression estimates at the 10th, 50th & 90th decile

	(1) 10th	(2) 50th	(3) 90th
<i>male</i>	0.412*** (23.68)	0.345*** (43.22)	0.138*** (10.49)
<i>spouse</i>	-0.0500** (-2.93)	0.166*** (16.35)	0.233*** (12.41)
<i>marrbef</i>	-0.293*** (-4.56)	0.0934*** (4.04)	0.224*** (5.44)
<i>chiim</i>	-0.0321 (-1.90)	-0.0659*** (-7.86)	-0.121*** (-7.47)
<i>age2635</i>	0.0330 (1.81)	0.226*** (20.46)	0.330*** (17.22)
<i>age3645</i>	-0.0421 (-1.56)	0.143*** (9.84)	0.294*** (10.39)
<i>age4655</i>	-0.0510 (-1.67)	0.0807*** (5.24)	0.167*** (6.12)
<i>age5665</i>	-0.194*** (-4.75)	-0.0600** (-3.20)	0.101*** (3.30)
<i>f3</i>	0.0838*** (4.11)	0.0856*** (8.43)	0.139*** (8.79)
<i>f5</i>	0.260*** (14.99)	0.204*** (19.69)	0.373*** (18.66)
<i>f7</i>	0.269*** (11.42)	0.291*** (13.40)	0.567*** (11.30)
<i>postsec</i>	0.336*** (15.62)	0.430*** (23.50)	1.298*** (21.61)
<i>undergrad</i>	0.297*** (11.75)	0.375*** (18.45)	1.715*** (25.21)
<i>postgrad</i>	0.326*** (10.59)	0.439*** (10.65)	2.282*** (13.90)
<i>manu</i>	-0.175*** (-7.81)	-0.231*** (-17.24)	-0.188*** (-7.41)
<i>egw</i>	0.0575 (1.15)	-0.0256 (-0.59)	-0.181* (-2.23)
<i>wrtrh</i>	0.0901*** (3.80)	-0.118*** (-7.64)	-0.137*** (-4.70)
<i>tsc</i>	0.0980*** (4.23)	-0.0126 (-0.73)	-0.128*** (-3.61)
<i>finance</i>	0.116*** (4.73)	-0.0714*** (-3.42)	-0.0574 (-1.26)
<i>socser</i>	0.0592* (2.33)	-0.0585*** (-3.82)	0.119*** (3.73)
<i>constant</i>	6.434*** (232.77)	6.952*** (451.60)	7.583*** (267.81)
<i>N</i>	18166	18166	18166
<i>adj. R²</i>	0.098	0.272	0.245

t statistics in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: 1986 unconditional quantile regression estimates at the 10th, 50th & 90th decile

	(1) 10th	(2) 50th	(3) 90th
<i>male</i>	0.513*** (22.52)	0.338*** (37.52)	0.153*** (8.61)
<i>spouse</i>	0.0341 (1.38)	0.171*** (15.33)	0.328*** (13.73)
<i>marrbef</i>	-0.0629 (-0.77)	0.109*** (3.89)	0.170*** (3.88)
<i>chiim</i>	-0.0797** (-3.25)	-0.105*** (-10.36)	-0.278*** (-13.05)
<i>age2635</i>	0.00734 (0.28)	0.344*** (27.59)	0.441*** (19.65)
<i>age3645</i>	0.0112 (0.30)	0.310*** (19.06)	0.643*** (18.06)
<i>age4655</i>	-0.0120 (-0.28)	0.208*** (11.13)	0.497*** (13.23)
<i>age5665</i>	-0.321*** (-5.34)	0.0318 (1.40)	0.386*** (9.74)
<i>f3</i>	0.184*** (5.78)	0.131*** (10.24)	0.217*** (11.45)
<i>f5</i>	0.456*** (16.66)	0.280*** (23.45)	0.525*** (21.68)
<i>f7</i>	0.479*** (13.37)	0.385*** (17.78)	0.829*** (14.75)
<i>postsec</i>	0.589*** (19.58)	0.530*** (30.98)	1.824*** (29.54)
<i>undergrad</i>	0.524*** (17.56)	0.512*** (29.12)	2.616*** (34.15)
<i>postgrad</i>	0.510*** (13.25)	0.462*** (11.41)	3.539*** (19.84)
<i>manu</i>	-0.0970* (-2.25)	-0.1000*** (-5.45)	-0.0613 (-1.94)
<i>egw</i>	0.174* (2.24)	0.231*** (6.15)	0.246* (2.07)
<i>wrtrh</i>	0.360*** (8.48)	0.0501* (2.56)	-0.0157 (-0.45)
<i>tsc</i>	0.315*** (6.98)	0.178*** (8.04)	-0.0688 (-1.63)
<i>finance</i>	0.376*** (8.75)	0.168*** (7.23)	0.165** (3.01)
<i>socser</i>	0.300*** (6.88)	0.209*** (10.75)	0.451*** (11.17)
<i>constant</i>	6.182*** (123.85)	6.865*** (322.83)	7.252*** (190.26)
<i>N</i>	20631	20631	20631
<i>adj. R²</i>	0.091	0.266	0.316

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: 1991 unconditional quantile regression estimates at the 10th, 50th & 90th decile

	(1) 10th	(2) 50th	(3) 90th
<i>male</i>	0.174*** (51.67)	0.284*** (79.26)	0.118*** (20.67)
<i>spouse</i>	0.0198*** (5.76)	0.170*** (37.28)	0.234*** (31.88)
<i>marrbef</i>	-0.0382** (-2.93)	0.113*** (9.99)	0.184*** (11.17)
<i>chiim</i>	-0.0437*** (-11.49)	-0.128*** (-29.74)	-0.176*** (-28.04)
<i>age2635</i>	0.0291*** (7.65)	0.283*** (52.54)	0.198*** (29.78)
<i>age3645</i>	0.00978 (1.90)	0.277*** (42.14)	0.420*** (42.15)
<i>age4655</i>	-0.0159* (-2.30)	0.146*** (18.12)	0.319*** (26.48)
<i>age5665</i>	-0.149*** (-15.76)	0.00999 (1.09)	0.261*** (21.76)
<i>f3</i>	0.0954*** (18.41)	0.136*** (24.92)	0.134*** (25.06)
<i>f5</i>	0.216*** (46.79)	0.363*** (69.21)	0.339*** (47.13)
<i>f7</i>	0.225*** (39.98)	0.548*** (66.03)	0.652*** (38.53)
<i>postsec</i>	0.238*** (46.00)	0.668*** (95.77)	1.099*** (61.50)
<i>undergrad</i>	0.232*** (45.84)	0.693*** (99.13)	1.712*** (77.82)
<i>postgrad</i>	0.221*** (28.17)	0.687*** (59.18)	2.445*** (44.03)
<i>manu</i>	-0.0349*** (-5.24)	-0.124*** (-16.08)	-0.00435 (-0.48)
<i>egw</i>	0.0717*** (6.33)	0.111*** (5.78)	0.130*** (3.53)
<i>wrtrh</i>	0.0823*** (12.55)	-0.0130 (-1.62)	0.0245* (2.53)
<i>tsc</i>	0.0736*** (10.74)	-0.0198* (-2.21)	-0.0174 (-1.60)
<i>finance</i>	0.0832*** (12.59)	0.0212* (2.43)	0.133*** (10.00)
<i>socser</i>	0.0400*** (5.85)	0.0336*** (4.17)	0.224*** (19.75)
<i>constant</i>	6.966*** (877.67)	7.132*** (780.99)	7.855*** (676.82)
<i>N</i>	102654	102654	102654
<i>adj. R²</i>	0.106	0.269	0.282

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: 1996 unconditional quantile regression estimates at the 10th, 50th & 90th decile

	(1) 10th	(2) 50th	(3) 90th
<i>male</i>	0.249*** (47.24)	0.200*** (58.26)	0.179*** (21.38)
<i>spouse</i>	0.0354*** (6.51)	0.134*** (30.63)	0.308*** (28.59)
<i>marrbef</i>	0.0240 (1.38)	0.0806*** (7.90)	0.257*** (11.11)
<i>chiim</i>	-0.119*** (-19.54)	-0.152*** (-37.56)	-0.261*** (-30.42)
<i>age2635</i>	0.0595*** (9.09)	0.307*** (56.42)	0.233*** (23.48)
<i>age3645</i>	0.0140 (1.70)	0.316*** (50.54)	0.638*** (47.36)
<i>age4655</i>	-0.0114 (-1.07)	0.238*** (31.74)	0.593*** (36.05)
<i>age5665</i>	-0.250*** (-15.21)	0.0778*** (8.40)	0.424*** (22.57)
<i>f3</i>	0.217*** (22.22)	0.123*** (22.09)	0.192*** (25.21)
<i>f5</i>	0.443*** (49.99)	0.412*** (76.60)	0.488*** (48.12)
<i>f7</i>	0.494*** (49.65)	0.583*** (76.28)	0.951*** (45.61)
<i>postsec</i>	0.511*** (52.74)	0.734*** (102.91)	1.553*** (60.04)
<i>undergrad</i>	0.523*** (58.47)	0.815*** (133.18)	2.120*** (91.50)
<i>postgrad</i>	0.497*** (50.29)	0.807*** (107.71)	3.259*** (67.87)
<i>manu</i>	-0.0402*** (-3.70)	-0.0838*** (-11.69)	-0.0145 (-1.14)
<i>egw</i>	0.149*** (7.72)	0.151*** (7.95)	0.143** (2.75)
<i>wrtrh</i>	0.0611*** (5.91)	-0.0653*** (-9.22)	-0.00351 (-0.28)
<i>tsc</i>	0.106*** (9.67)	-0.0114 (-1.43)	-0.0560*** (-4.02)
<i>finance</i>	0.0970*** (9.28)	0.0166* (2.20)	0.157*** (9.45)
<i>socser</i>	0.0452*** (4.24)	0.0509*** (7.08)	0.287*** (19.29)
<i>constant</i>	6.845*** (509.81)	7.282*** (834.22)	7.594*** (468.86)
<i>N</i>	118282	118282	118282
<i>adj. R²</i>	0.101	0.271	0.272

t statistics in parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: 2001 unconditional quantile regression estimates at the 10th, 50th & 90th decile

	(1) 10th	(2) 50th	(3) 90th
<i>male</i>	0.362*** (24.02)	0.248*** (26.34)	0.205*** (11.92)
<i>spouse</i>	0.0384* (2.44)	0.155*** (12.63)	0.290*** (12.46)
<i>marrbef</i>	0.0365 (0.80)	0.0424 (1.65)	0.222*** (5.16)
<i>chiim</i>	-0.137*** (-7.53)	-0.203*** (-17.89)	-0.205*** (-11.91)
<i>age2635</i>	0.267*** (11.68)	0.515*** (33.82)	0.159*** (7.85)
<i>age3645</i>	0.220*** (8.53)	0.585*** (34.81)	0.604*** (22.72)
<i>age4655</i>	0.221*** (7.26)	0.524*** (27.04)	0.647*** (20.20)
<i>age5665</i>	0.00523 (0.11)	0.291*** (10.82)	0.498*** (11.37)
<i>f3</i>	0.351*** (11.43)	0.166*** (10.60)	0.185*** (13.90)
<i>f5</i>	0.691*** (24.59)	0.518*** (33.76)	0.466*** (23.66)
<i>f7</i>	0.637*** (18.40)	0.713*** (34.26)	0.799*** (21.12)
<i>postsec</i>	0.844*** (28.31)	0.962*** (48.73)	1.306*** (27.32)
<i>undergrad</i>	0.851*** (29.98)	1.095*** (63.86)	2.021*** (45.96)
<i>postgrad</i>	0.811*** (27.06)	1.091*** (52.77)	3.322*** (38.97)
<i>manu</i>	-0.0527 (-1.61)	-0.0467* (-2.11)	0.0334 (1.19)
<i>egw</i>	0.116** (2.83)	0.315*** (6.66)	0.221* (2.02)
<i>wrtrh</i>	-0.0941** (-3.10)	-0.121*** (-6.04)	0.0596** (2.60)
<i>tsc</i>	0.0410 (1.30)	-0.0237 (-1.05)	-0.0137 (-0.52)
<i>finance</i>	0.0245 (0.82)	-0.00774 (-0.37)	0.168*** (5.34)
<i>socser</i>	-0.156*** (-4.93)	0.0888*** (4.32)	0.328*** (11.94)
<i>constant</i>	6.546*** (156.30)	7.040*** (284.33)	7.731*** (242.40)
<i>N</i>	25175	25175	25175
<i>adj. R²</i>	0.107	0.303	0.301

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: 2006 unconditional quantile regression estimates at the 10th, 50th & 90th decile

	(1) 10th	(2) 50th	(3) 90th
<i>male</i>	0.219*** (17.08)	0.162*** (19.76)	0.168*** (8.73)
<i>spouse</i>	0.0276* (2.01)	0.141*** (13.26)	0.389*** (14.97)
<i>marrbef</i>	-0.0153 (-0.42)	0.0469* (2.21)	0.279*** (6.20)
<i>chiim</i>	-0.213*** (-12.76)	-0.243*** (-24.65)	-0.269*** (-14.43)
<i>age2635</i>	0.394*** (17.77)	0.520*** (37.92)	0.0521* (2.45)
<i>age3645</i>	0.354*** (14.44)	0.568*** (38.26)	0.580*** (19.98)
<i>age4655</i>	0.354*** (12.90)	0.493*** (29.66)	0.619*** (18.24)
<i>age5665</i>	0.276*** (7.04)	0.409*** (18.37)	0.547*** (12.56)
<i>f3</i>	0.221*** (7.60)	0.129*** (8.53)	0.152*** (8.93)
<i>f5</i>	0.455*** (17.08)	0.396*** (27.11)	0.445*** (19.60)
<i>f7</i>	0.393*** (11.69)	0.496*** (25.59)	0.729*** (18.73)
<i>postsec</i>	0.610*** (21.82)	0.657*** (36.60)	1.084*** (24.14)
<i>undergrad</i>	0.651*** (24.13)	0.858*** (53.75)	1.849*** (41.66)
<i>postgrad</i>	0.603*** (21.48)	0.852*** (46.17)	2.961*** (36.60)
<i>manu</i>	-0.0140 (-0.49)	-0.0238 (-1.17)	0.155*** (4.30)
<i>egw</i>	0.00658 (0.12)	0.193*** (3.98)	0.352* (2.26)
<i>wrtrh</i>	-0.0657* (-2.54)	-0.0676*** (-3.78)	0.119*** (4.22)
<i>tsc</i>	-0.0144 (-0.52)	-0.00715 (-0.36)	0.0494 (1.60)
<i>finance</i>	0.0409 (1.62)	-0.00181 (-0.10)	0.323*** (9.12)
<i>socser</i>	-0.188*** (-6.90)	-0.00537 (-0.30)	0.339*** (10.67)
<i>constant</i>	6.655*** (168.36)	7.196*** (308.20)	7.622*** (200.40)
<i>N</i>	26234	26234	26234
<i>adj. R²</i>	0.091	0.271	0.250

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Decomposition of changes in wage dispersion at the 10th, 50th & 90th decile from 1981 to 1986

	10th			50th			90th		
	C effect	WS effect	T effect	C effect	WS effect	T effect	C effect	WS effect	T effect
<i>male</i>	-0.2959	0.0602	-0.2357	-0.0730	0.1037	0.0307	-0.1504	0.2053	0.0549
<i>spouse</i>	0.0321	0.0560	0.0880	0.0153	0.0095	0.0249	0.1663	0.0070	0.1733
<i>marrbef</i>	0.2547	0.0994	0.3542	-0.0053	0.0336	0.0283	0.5197	-0.5217	-0.0020
<i>chiim</i>	0.3126	-0.3064	0.0062	0.4391	-0.3876	0.0515	0.7914	-0.5764	0.2149
<i>age2635</i>	0.5078	-0.5475	-0.0397	0.8129	-0.6558	0.1571	0.5492	-0.3311	0.2181
<i>age3645</i>	0.7166	-0.6533	0.0632	0.9930	-0.7898	0.2032	1.2907	-0.8048	0.4859
<i>age4655</i>	0.7146	-0.6537	0.0609	0.9200	-0.7689	0.1511	1.1294	-0.7009	0.4285
<i>age5665</i>	0.8817	-0.8203	0.0614	1.0258	-0.9301	0.0957	1.2806	-0.9222	0.3584
<i>f3</i>	0.3940	-0.3930	0.0010	0.5868	-0.5260	0.0608	0.3432	-0.2156	0.1275
<i>f5</i>	0.3444	-0.4116	-0.0672	0.7923	-0.6832	0.1090	0.7241	-0.4467	0.2775
<i>f7</i>	0.3833	-0.4481	-0.0648	0.8064	-0.6679	0.1385	1.0829	-0.6252	0.4578
<i>postsec</i>	0.3133	-0.3998	-0.0864	0.9772	-0.8164	0.1608	1.9332	-0.9701	0.9631
<i>undergrad</i>	0.2403	-0.3151	-0.0748	0.9329	-0.7370	0.1959	1.5268	-0.0149	1.5119
<i>postgrad</i>	0.1551	-0.2770	-0.1219	0.8975	-0.8217	0.0759	1.4779	0.6016	2.0796
<i>manu</i>	-0.2110	0.0366	-0.1744	-0.2105	0.0908	-0.1197	-0.1129	0.0161	-0.0967
<i>egw</i>	0.1250	-0.0948	0.0302	0.2138	0.0698	0.2836	-0.0037	0.4507	0.4470
<i>wrtrh</i>	0.2103	-0.1091	0.1012	0.4367	-0.2626	0.1740	0.3088	-0.2050	0.1038
<i>tsc</i>	0.0785	-0.0155	0.0630	0.1636	0.0478	0.2114	-0.1416	0.1762	0.0346
<i>finance</i>	-0.0230	0.0999	0.0768	0.2232	0.0362	0.2595	0.2706	-0.0278	0.2428
<i>socser</i>	0.0443	0.0615	0.1058	0.1823	0.1101	0.2924	0.3266	0.0914	0.4180
<i>constant</i>	-0.0639	0.1403	0.0764	-0.2331	0.0759	-0.1571	0.7715	-1.3128	-0.5412
Total	5.1148	-4.8913	0.2234	9.8969	-7.4696	2.4275	14.0843	-6.1269	7.9577

Table 20: Decomposition of changes in wage dispersion at the 10th, 50th & 90th decile from 1986 to 1991

	10th			50th			90th		
	C effect	WS effect	T effect	C effect	WS effect	T effect	C effect	WS effect	T effect
<i>male</i>	-0.3696	0.0036	-0.3660	-0.2706	0.2217	-0.0489	0.1516	-0.1133	0.0383
<i>spouse</i>	-0.0410	0.0242	-0.0168	0.0375	-0.0346	0.0029	0.0652	-0.0039	0.0613
<i>marrbef</i>	-0.0910	0.1206	0.0296	-0.2009	0.2072	0.0063	0.3015	-0.2016	0.1000
<i>chiim</i>	0.1207	-0.1624	-0.0417	0.3384	-0.3112	0.0271	0.8108	-0.7833	0.0276
<i>age2635</i>	0.8536	-0.8346	0.0190	0.8916	-0.9483	-0.0567	0.1279	-0.1734	-0.0455
<i>age3645</i>	1.0363	-1.0388	-0.0025	1.5702	-1.5975	-0.0273	2.0730	-1.9964	0.0766
<i>age4655</i>	0.9390	-0.9412	-0.0022	1.3415	-1.4017	-0.0602	2.3699	-2.3171	0.0528
<i>age5665</i>	1.3125	-1.1193	0.1932	1.6720	-1.6944	-0.0224	2.7445	-2.6885	0.0559
<i>f3</i>	0.4045	-0.5055	-0.1009	0.8060	-0.7981	0.0079	0.5950	-0.5769	0.0181
<i>f5</i>	0.1414	-0.4113	-0.2699	0.9554	-0.8606	0.0948	1.5777	-1.5192	0.0585
<i>f7</i>	0.1024	-0.3875	-0.2851	1.0096	-0.8265	0.1830	1.3967	-1.1759	0.2208
<i>postsec</i>	0.0655	-0.4509	-0.3854	1.2274	-1.0671	0.1603	1.1105	-0.9947	0.1159
<i>undergrad</i>	0.1104	-0.4347	-0.3243	1.3320	-1.1258	0.2061	2.6880	-2.3723	0.3157
<i>postgrad</i>	0.1654	-0.4861	-0.3207	1.5029	-1.2513	0.2516	3.2630	-2.6940	0.5690
<i>manu</i>	0.5473	-0.6147	-0.0674	0.5342	-0.5066	0.0276	0.5816	-0.6134	-0.0319
<i>egw</i>	-0.2549	0.1425	-0.1125	-0.8554	0.7332	-0.1221	-1.2103	1.2061	-0.0043
<i>wrtrh</i>	-0.1737	-0.1190	-0.2927	-0.1964	0.1303	-0.0661	-0.3826	0.4189	0.0362
<i>tsc</i>	-0.0837	-0.1711	-0.2549	-0.0235	-0.1830	-0.2066	-0.4329	0.4550	0.0221
<i>finance</i>	-0.1371	-0.1720	-0.3091	0.1900	-0.3425	-0.1525	1.2142	-1.1665	0.0477
<i>socser</i>	-0.2447	-0.0255	-0.2703	-0.2828	0.1007	-0.1821	-0.9767	0.9531	-0.0236
<i>constant</i>	1.0822	-0.2609	0.8214	0.8799	-0.6305	0.2493	2.1706	-2.0493	0.1213
Total	5.4855	-7.8446	-2.3592	12.459	-12.1866	0.272	20.2392	-18.4066	1.8325

Table 21: Decomposition of changes in wage dispersion at the 10th, 50th & 90th decile from 1991 to 1996

	10th			50th			90th		
	C effect	WS effect	T effect	C effect	WS effect	T effect	C effect	WS effect	T effect
<i>male</i>	-0.0766	0.0303	-0.0463	-0.1801	0.1096	-0.0705	0.0559	0.0217	0.0776
<i>spouse</i>	0.04758	-0.0465	0.0011	0.0051	-0.0326	-0.0275	0.2008	-0.0984	0.1024
<i>marrbef</i>	0.2296	-0.1488	0.0808	0.1215	-0.1480	-0.0266	0.3873	-0.2894	0.0979
<i>chiim</i>	0.1963	-0.1569	0.0394	0.2314	-0.1960	0.0353	0.4799	-0.3701	0.1098
<i>age2635</i>	0.3476	-0.3394	0.0082	0.4055	-0.3585	0.0471	-0.1274	0.1831	0.0557
<i>age3645</i>	0.6299	-0.6325	-0.0026	0.8340	-0.7722	0.0619	0.8782	-0.6001	0.2781
<i>age4655</i>	0.7986	-0.7842	0.01446	0.9757	-0.8659	0.1098	1.0161	-0.6838	0.3322
<i>age5665</i>	0.4586	-0.4519	0.0067	0.8088	-0.7343	0.0744	0.6907	-0.4869	0.2039
<i>f3</i>	0.6518	-0.6048	0.0470	0.5406	-0.5446	-0.0040	0.2476	-0.1725	0.0751
<i>f5</i>	0.7422	-0.6801	0.0621	0.6345	-0.5552	0.0793	0.4888	-0.2940	0.1948
<i>f7</i>	0.8092	-0.7154	0.0938	0.8182	-0.7403	0.0779	1.0646	-0.6762	0.3884
<i>postsec</i>	0.7111	-0.6217	0.0894	0.5932	-0.4731	0.1202	0.2568	0.3430	0.5999
<i>undergrad</i>	0.8021	-0.6924	0.1097	1.0179	-0.8355	0.1823	3.2976	-2.6955	0.6021
<i>postgrad</i>	0.7389	-0.6356	0.1032	0.9835	-0.8038	0.1797	6.4328	-5.3164	1.1164
<i>manu</i>	1.1143	-1.1323	-0.0180	0.7131	-0.7474	-0.0343	0.3455	-0.3339	0.0116
<i>egw</i>	-0.3410	0.3631	0.0221	-0.4981	0.5500	0.0519	-0.0558	0.0814	0.0256
<i>wrtrh</i>	-0.1304	0.0576	-0.0728	-0.2581	0.2003	-0.0578	-0.1419	0.1130	-0.0289
<i>tsc</i>	-0.1730	0.1537	-0.0194	-0.2502	0.2579	0.0077	-0.1916	0.1472	-0.0444
<i>finance</i>	-0.2477	0.2056	-0.0422	-0.2461	0.2426	-0.0035	0.1276	-0.0898	0.0378
<i>socser</i>	-0.3451	0.3236	-0.0215	-0.3762	0.3975	0.0213	-0.2653	0.3550	0.0897
<i>constant</i>	-0.1260	0.1949	0.0689	0.3205	-0.2204	0.1001	0.5960	-0.9752	-0.3792
Total	6.8380	-6.3137	0.5241	7.1947	-6.2699	0.9247	15.7842	-11.8378	3.9465

Table 22: Decomposition of changes in wage dispersion at the 10th, 50th & 90th decile from 1996 to 2001

	10th			50th			90th		
	C effect	WS effect	T effect	C effect	WS effect	T effect	C effect	WS effect	T effect
<i>male</i>	-0.1763	0.2237	0.0474	-0.1910	0.3319	0.1409	-0.1062	0.1762	0.0700
<i>spouse</i>	-0.1547	0.1505	-0.0043	-0.1978	0.2769	0.0791	-0.1944	0.2410	0.0466
<i>marrbef</i>	-0.0024	0.0083	0.0059	-0.0453	0.0219	-0.0235	0.0060	0.0083	0.0143
<i>chiim</i>	0.1527	-0.1606	-0.0080	0.1553	-0.0287	0.1267	0.2129	-0.2223	-0.0094
<i>age2635</i>	0.1208	0.0431	0.1639	0.1306	0.2731	0.4037	-0.2071	0.1698	-0.0373
<i>age3645</i>	0.4663	-0.2948	0.1715	0.5792	-0.0875	0.4917	0.6902	-0.5897	0.1005
<i>age4655</i>	0.7784	-0.5797	0.1987	0.8976	-0.4105	0.4872	1.1980	-1.0030	0.1950
<i>age5665</i>	0.2632	-0.00002	0.2632	0.5645	-0.2384	0.3262	0.7050	-0.5238	0.1813
<i>f3</i>	0.2804	-0.2093	0.0711	0.2795	-0.1745	0.1050	0.2658	-0.2308	0.0349
<i>f5</i>	0.3765	-0.2518	0.1247	0.3241	-0.0228	0.3013	0.4325	-0.3507	0.0818
<i>f7</i>	0.4427	-0.4167	0.0261	0.4469	-0.0494	0.3975	0.5792	-0.5507	0.0284
<i>postsec</i>	0.5005	-0.3171	0.1834	0.5289	0.0611	0.5900	0.7381	-0.6897	0.0485
<i>undergrad</i>	0.5248	-0.3491	0.1758	0.6061	0.0859	0.6920	1.1377	-0.7876	0.3501
<i>postgrad</i>	0.4943	-0.3248	0.1695	0.6458	0.0487	0.6945	2.0666	-1.2712	0.7949
<i>manu</i>	0.8506	-0.8479	0.0028	0.3487	-0.3694	-0.0207	0.1896	-0.2435	-0.0539
<i>egw</i>	-0.0893	0.0334	-0.0559	-0.3186	0.6025	0.2839	-0.2831	0.4080	0.1249
<i>wrtrh</i>	0.1625	-0.3053	-0.1428	0.1099	-0.2121	-0.1022	0.0947	-0.0203	0.0745
<i>tsc</i>	0.0544	-0.1293	-0.0749	0.0283	-0.0496	-0.0213	0.0466	-0.0085	0.0381
<i>finance</i>	0.0748	-0.1546	-0.0798	0.1539	-0.1816	-0.0277	0.2847	-0.2364	0.0483
<i>socser</i>	0.0272	-0.2056	-0.1784	0.0906	-0.0191	0.0715	0.0616	0.0501	0.1117
<i>constant</i>	-0.4124	0.2632	-0.1492	-0.2179	-0.4348	-0.6527	0.0820	-0.2489	-0.1669
Total	4.735	-3.8244	0.9107	4.9193	-0.5764	4.3431	8.0004	-5.9237	2.0763

Table 23: Decomposition of changes in wage dispersion at the 10th, 50th & 90th decile from 2001 to 2006

	10th			50th			90th		
	C effect	WS effect	T effect	C effect	WS effect	T effect	C effect	WS effect	T effect
<i>male</i>	-0.1133	0.0171	-0.0962	-0.1261	0.0344	-0.0917	-0.0827	0.0280	-0.0546
<i>spouse</i>	-0.1385	0.1330	-0.0055	-0.2041	0.1845	-0.0196	-0.1822	0.2442	0.0621
<i>marrbef</i>	0.1229	-0.1730	-0.0500	0.0877	-0.0850	0.0027	-0.0663	0.0966	0.0303
<i>chiim</i>	0.1955	-0.0923	0.1032	0.1361	-0.1060	0.0301	0.1524	-0.1143	0.0381
<i>age2635</i>	0.1473	0.0321	0.1794	0.0167	-0.0322	-0.0155	-0.1316	0.0164	-0.1152
<i>age3645</i>	0.2657	-0.0862	0.1795	0.2836	-0.3226	-0.0390	0.1040	-0.1879	-0.0839
<i>age4655</i>	0.6557	-0.4770	0.1787	0.6769	-0.7269	-0.0500	0.3970	-0.4895	-0.0925
<i>age5665</i>	0.9262	-0.6332	0.2930	0.8387	-0.7376	0.1011	0.4279	-0.4330	-0.0051
<i>f3</i>	0.6951	-0.7789	-0.0838	0.4231	-0.4650	-0.0419	0.0600	-0.1098	-0.0498
<i>f5</i>	0.7952	-0.9390	-0.1438	0.5464	-0.6831	-0.1367	0.0371	-0.1046	-0.0675
<i>f7</i>	0.6941	-0.8552	-0.1611	0.4778	-0.7125	-0.2347	-0.1642	0.0167	-0.1475
<i>postsec</i>	0.7939	-0.9117	-0.1178	0.7554	-1.084	-0.3287	0.1676	-0.5085	-0.3410
<i>undergrad</i>	0.7795	-0.8581	-0.0786	0.8091	-1.0773	-0.2683	0.1013	-0.4691	-0.368
<i>postgrad</i>	0.7364	-0.8309	-0.0945	0.7275	-0.9984	-0.2709	1.1892	-1.867	-0.6775
<i>manu</i>	0.3824	-0.4157	-0.0332	0.2287	-0.2523	-0.0236	0.2841	-0.3933	-0.1093
<i>egw</i>	-0.1897	0.0902	-0.0995	-0.3769	0.2480	-0.1290	-0.3286	0.4273	0.0987
<i>wrtrh</i>	0.0140	0.0016	0.0155	0.0630	-0.0071	0.0559	-0.0546	0.1034	0.0488
<i>tsc</i>	-0.0071	-0.0460	-0.0531	0.0208	-0.0040	0.0167	-0.0373	0.0972	0.0600
<i>finance</i>	-0.0593	0.0809	0.0215	-0.0131	0.0191	0.0060	-0.2270	0.3531	0.1261
<i>socser</i>	-0.0310	-0.0282	-0.0592	-0.0642	-0.0291	-0.0932	-0.0735	0.0502	-0.0233
<i>constant</i>	-0.1402	0.1246	-0.0156	0.1068	0.0813	0.1881	0.7699	-0.7280	0.0419
Total	6.5248	-6.6459	-0.1211	5.4139	-6.7558	-1.3422	2.3425	-3.9719	-1.6292

Figure 1: Kernel density estimation of real wage distributions for all census and by-census years since 1981

Figure 2: Kernel density estimation of real wage distributions in 1981, 1986 and counterfactual distribution

Figure 3: Kernel density estimation of real wage distributions in 1986, 1991 and counterfactual distribution

Figure 4: Kernel density estimation of real wage distributions in 1991, 1996 and counterfactual distribution

Figure 5: Kernel density estimation of real wage distributions in 1996, 2001 and counterfactual distribution

Figure 6: Kernel density estimation of real wage distributions in 2001, 2006 and counterfactual distribution

Figure 7: Unconditional quantile regression coefficients in 1981

Figure 8: Unconditional quantile regression coefficients in 1986

Figure 9: Unconditional quantile regression coefficients in 1991

Figure 10: Unconditional quantile regression coefficients in 1996

Figure 11: Unconditional quantile regression coefficients in 2001

Figure 12: Unconditional quantile regression coefficients in 2006

Figure 13: Decomposition of total log wage change across quantiles into composition effect and wage structure effect from 1981 to 1986

Figure 14: Decomposition of total log wage change across quantiles into composition effect and wage structure effect from 1986 to 1991

Figure 15: Decomposition of total log wage change across quantiles into composition effect and wage structure effect from 1991 to 1996

Figure 16: Decomposition of total log wage change across quantiles into composition effect and wage structure effect from 1996 to 2001

Figure 17: Decomposition of total log wage change across quantiles into composition effect and wage structure effect from 2001 to 2006

Figure 18: Decomposition of total effects of covariates across quantiles into composition and wage structure effect from 1981 to 1986

—●— Total effect —■— Composition effect —+— WageStructure effect

Figure 19: Decomposition of total effects of covariates across quantiles into composition and wage structure effect from 1986 to 1991

Figure 20: Decomposition of total effects of covariates across quantiles into composition and wage structure effect from 1991 to 1996

—●— Total effect —■— Composition effect —+— WageStructure effect

Figure 21: Decomposition of total effects of covariates across quantiles into composition and wage structure effect from 1996 to 2001

—●— Total effect —■— Composition effect —+— WageStructure effect

Figure 22: Decomposition of total effects of covariates across quantiles into composition and wage structure effect from 2001 to 2006

—●— Total effect —■— Composition effect —+— WageStructure effect

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