THREE ESSAYS ON EARNINGS AND EARNINGS INEQUALITY IN HONG KONG: 1991-2011

by

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THREE ESSAYS ON EARNINGS AND EARNINGS INEQUALITY

IN HONG KONG: 1991-2011

by

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ABSTRACT

The main goal of this study is to use 5% sample of the Hong Kong population census and by-census datasets to examine three features of earnings in Hong Kong: overall earnings inequality; gender earnings gap; and earnings differences between immigrants and natives. By conducting a counterfactual analysis, I find that a significant portion of the changes in earnings inequality is due to the changes in observed individual characteristics and the changes in return to skills. Over time, the gender earnings gap widened especially at the lower percentiles of the earnings distribution. The Oaxaca-Blinder decomposition estimates suggest that more than one third of the gender earnings gap at the mean level could be accounted for by the covariate differences. The earnings differential between natives and immigrants tends to be higher at both lower and upper percentiles. By applying the Recentered Influence Function method, I observe that occupational segregation plays an important role in explaining the earnings gap for both the lower and upper percentiles. The difference in educational attainment between Chinese immigrants and natives is responsible for limiting occupational mobility among Chinese immigrants in Hong Kong.

Chapter 1

INTRODUCTION

Hong Kong is one of the most densely populated regions and also one of the most competitive economy entities in the world. It has maintained a stable economic system under the principle of "one country, two systems" after the sovereignty transfer from Great Britain to China. Since the 1950s, Hong Kong has experienced rapid economic growth and GDP per capita has more than tripled in real terms (Zhao, Zhang, and Sit Tak O 2004). More recently, Hong Kong has become one of the richest economies with GDP per capita of more than $35,000 in 2011 (World Bank 2015). Nevertheless, Hong Kong also has income inequality that is among the highest in advanced economies. According to the Thematic Report published by the Census and Statistics Department of Hong Kong (2012b), Hong Kong had a higher Gini coefficient (0.475) based on post-tax post-social transfer monthly household income, than some OECD countries, like United States (0.389), Germany (0.293), France (0.309), etc. (OECD.Stat 2015). Rising public awareness on this issue ignited social instability like the "Umbrella Movement", a serious political unrest that occurred in 2014.

In addition, two other features of Hong Kong's labor market are quite interesting. Firstly, the role of gender in a Chinese-society like Hong Kong is complex. On one hand, Hong Kong is substantially influenced by traditional Confucian thought. Historically, women were restricted by the rule of "three obediences and four virtues" under which women oversaw household affairs while men dominated external affairs (Internet Encyclopedia of Philosophy 2017) [1]. Women in Hong Kong presently still have a big burden of household affairs such as parenting responsibilities, house cleaning, laundry etc. On the other hand, a lot of women have participated in the labor market in Hong Kong more recently. One reason is that many career opportunities, including prestigious occupations dominated by males in the past, have been open for females now. The other reason is the burden of living cost, especially the housing. Due to the high demand and low supply of land, home prices soared significantly in Hong Kong (Ho and Campbell 2017). Under such circumstance, many women in Hong Kong have to work outside and take partial or full responsibility of the family. To some extent, women in Hong Kong are in a dilemma over careers and families (Tai 2013).

Secondly, Hong Kong is a society of immigrants with a large number of immigrants predominantly from mainland China. In 2011, 60.5% of the Hong Kong population (approximately 7.07 million) was native born. 32.1% of the population was born in mainland China, Macao and Taiwan (Census and Statistics Department of Hong Kong 2012b). In other words, people of Chinese descent comprised the vast majority of the population of Hong Kong. In addition, Chinese immigrants and Hong Kong natives are ethnically homogeneous, sharing language and culture. No doubt that Chinese immigrants have made great contributions to both the labor supply and innovation and technological change in Hong Kong. Thus, immigrants in Hong Kong are essential to Hong Kong's long-term sustained economic growth.

[1] The three obediences for a woman to obey were: 1) her father as a daughter; 2) her husband as a wife; 3) her sons in widowhood. The four feminine virtues were: 1) wifely virtue; 2) wifely speech; 3) wifely manner/appearance; 4) wifely work.

As one of the most densely populated regions and also one of the most competitive economy entities in the world, Hong Kong is an ideal place for earnings inequality study. Apparently, Hong Kong's high level of income inequality is threatening the stability of society, and has limited social mobility. In the meantime, Hong Kong is faced with demographic challenges including low birth rates and an elderly problem. By understanding how earnings inequality evolves and its underlying determinants, people can come up with better solutions to fight against the earnings gap and achieve sustained economic growth in Hong Kong. Thus, it is necessary to examine income inequality and its sources in Hong Kong.

Relatively little is known about earnings inequality and its driving force in Hong Kong. In this study, I will use the 5% samples of the 5 population census and by-census datasets over the period from 1991 to 2011 to examine three features of earnings in Hong Kong: earnings inequality and its underlying sources; gender earnings gap; and earnings differences between immigrants and natives. The unusual and rich data will allow me to explicitly examine how income disparity evolved over a 20-year period, and investigate the underlying sources of income disparity through multiple decomposition methods in counterfactual manners.

Chapter 2

DATA

In this study, the datasets include the 5% sample of the Hong Kong population census and by-census datasets for the years 1991, 1996, 2001, 2006 and 2011. The population census/by-census in Hong Kong is conducted by the Census and Statistics Department. The census has been held every ten years since 1961 and the by-census is conducted midway between two censuses [2]. Throughout this study, I focus on the log of monthly earnings in real terms using 2011 as the reference year. For household-level data, income variable is monthly domestic income including earnings in cash from all employment and other cash incomes of all members of economically active households. For individual-level data, income is each economically active individual's monthly income from all employment. In my empirical analysis, I also restrict individuals to ages 15-65.

For most individuals and households, income information is precisely recorded, however top earners' income is top-coded. For instance, in the 2011 population census top-coding applied to incomes at or above HK$ 150,000. This implies that the upper income category is open-ended. Researchers had applied different measures, such as the lower limit of the open-ended category or the Pareto

[2] According to the Census Department, a by-census only differs from a census in not having a complete headcount of the population. They both collect detailed characteristics, including demographic, educational and economic of a large sample of the population.

distribution, to estimate the midpoint of the open-ended income category (Parker and Fenwick 1983). After reviewing the dataset, I noticed that the number of individuals in the open-ended income category was relatively small as a percentage of the total observations. For example, 1,252 people were coded with an income of HK$150,000 in 2011, which is approximately 0.69% of the total observations. Therefore, in this study I assume the top group of individuals and households have earnings two times the threshold, following the technique used by Hoffman et al (2012) [3]. Using 2011 data as an example, I assume all the top income earners have an average income of HK$ 300,000 in 2011.

In the empirical analysis, a set of variables are considered as potential explanatory variables, including 1) Age; 2) Gender; 3) Education, measured as years of schooling; 4) Potential Work Experience, defined as Age-Education-6; 5) Place of Birth; 6) Duration of Residence in Hong Kong, defined as the total number of complete years for which a person has lived in Hong Kong; 7) Occupation, which refers to the kind of work a person performed during the seven days before the census/by-census reference moment.

[3] In the later discussions, I also present statistics using earnings three times the threshold and four times the threshold.

Chapter 3

INCOME INEQUALITY IN HONG KONG: 1991-2011

3.1 Introduction

Income inequality remains at record-high levels since the mid-1980s in most OECD countries (OECD 2016). In the mid-1980s, the richest 10% were 7 times more income than the poorest 10%, and today it is 10 times more. Many developing countries in Asia and Sub-Saharan Africa have also seen a growing gap between rich and poor. For instance, income inequality rose by about 1.6% a year since 1990 (Keeley 2015). High levels of inequality are likely to reduce people's opportunities to access high-quality education and limit economic and social mobility, thus reduce the long-term economic growth (Corak 2013). Moreover, rising inequality may threaten the stability of societies and create social unrest (Keeley 2015). Certainly, higher inequality generates great cost for societies. Therefore, rising income inequality has become a concern of not only economists but also politicians and the public.

Due to the lack of micro-level data, studies on earnings and earnings inequality in Hong Kong are limited. Most previous studies reached a consensus that the earnings inequality in Hong Kong has been staying at a high level, and that income inequality, as measured by the Gini coefficient, is rising (K. Cheung and Fan 2002; Fan and Cheung 2004; Lam and Liu 2002; Liu, Zhang, and Chong 2004). The investigation of sources of earnings inequality is somewhat limited since those studies mainly focused on the effect of trade and immigrants on earnings inequality. In practice, measurements other than the Gini coefficient, such as the income share captured by the top 1% households, the 90-10 log wage differentials, etc., are useful as well in describing income inequality. Moreover, researchers have discussed the relative importance of observed characteristics and unobservables to earnings inequality (Katz and Murphy 1992; Juhn, Murphy, and Pierce 1993; Lemieux 2006; Autor, Katz, and Kearney 2008; Autor 2014). In a standard Mincer wage equation, in which wage is modeled as a function of observed characteristics including education, experience, etc., and an error term, the between-group inequality is captured by the distribution of these observed characteristics and their coefficients, and the within-group or residual inequality is captured by the error term. Therefore, explaining how between-/within-group inequality evolves and their underlying determinants are important for understanding earnings inequality in Hong Kong.

One way to look at the between-group inequality and its determinants is to apply a decomposition method. This approach decomposes the changes in wage inequality into three components: changes in the price of skills, changes in the distribution of characteristics, and changes in the distribution of the residuals (Juhn et al. 1993). Together with a counterfactual analysis, we can examine the effect of each component on the wage inequality separately. This idea can be traced back to the 1970s when Oaxaca (1973) and Blinder (1973) studied gender inequality. They performed a counterfactual analysis estimating what the wage distribution of females would look like if females have the same distribution of skills as males do. Similarly, we can generate a counterfactual wage distribution by holding fixed some subset of components. Another way to explain the between-group inequality is to apply a demand-supply framework (Katz and Murphy 1992; Goldin and Katz 2008; Autor 2014). This framework concentrates on skill premiums, i.e. the price of skills, as demand and supply of labor are compared. In economics, if supply does not keep pace with demand, then price would rise. Therefore, this framework is useful when explaining changes in income inequality. With regard to the demand for skills, some studies claimed that computerization and skill-biased technological changes (SBTC) are two main sources driving the growth in the demand for skilled workers (Card and DiNardo 2002; Autor, Levy, and Murnane 2003; Autor et al. 2008).

The study of within-group or residual inequality is important, as a large proportion of wage variation cannot be explained by observed characteristics and skill prices (Juhn et al. 1993; Lemieux 2006; Xing and Li 2012). The study of residual inequality has concentrated on the role of the composition effect in explaining the changes in the within-group inequality. To examine the influence of the composition effect, a counterfactual analysis has been widely used in the studies of within-group inequality. When explaining the residual inequality, researchers tend to use residual gaps such as 90-10 residual differential, or residual variance as the dependent variables (Lemieux 2006; Xing and Li 2012). In this study, composition effect represents the influence of unobserved skill distribution to the within-group inequality. It is estimated as the actual residual variance minus the counterfactual variance by holding skills distribution at a certain year.

In this study, I use the 5% sample of the Hong Kong population census and by-census datasets for the years 1991 to 2011 to investigate the trend of earnings inequality in Hong Kong and its underlying determinants. For descriptive statistics, I discuss overall and residual earnings inequality in detail, using different measures such as the income share of each quintile of individuals, income distribution, and between-group income differentials. For the study of overall inequality, first I decompose the changes in income inequality into three components--changes in the price of skills, changes in the distribution of characteristics, and changes in the distribution of the residuals. Then I perform a counterfactual analysis. Meanwhile, I use a demand-supply framework to discuss the implication of the economic restructuring to skill prices. For the study of residual inequality, I perform a variance decomposition and a counterfactual analysis to examine the trend of within-group inequality and its underlying sources.

This work makes three important contributions. Prior to this study, no empirical work has examined earnings inequality in Hong Kong and its underlying determinants. In this study, I examine earnings inequality in different ways, and examine the effect of changes in the return to skills, changes in the distribution of characteristics, and changes in the unobservables on earnings inequality separately. I also examine the impact of the composition effect on residual inequality. Second, I find that a significant portion of the changes in earnings inequality is due to the changes in the observables, and this finding is different from that of previous studies which have typically found that changes in the unobservables account for a big portion of the changes in earnings inequality (Juhn et al. 1993; Lemieux 2006; Xing and Li 2012). However, the impact of the composition effect is consistent with previous studies, as it is powerful at explaining the changes in within-group inequality. Last, I provide additional evidence that applying the decomposition method and conducting counterfactual analyses to the study of earnings inequality would be very useful.

This chapter is organized as follows. Section 3.2 presents the descriptive statistics of income inequality in Hong Kong with alternative measures. Section 3.3 applies a decomposition method to the changes in income inequality, and examines the importance of changes in the distribution of skills, changes in the skill prices and the unobservables, separately. Section 3.4 decomposes the residual variance and performs a counterfactual analysis to examine the influence of composition effect on residual inequality.

3.2 Inequality Facts

3.2.1 Income Shares

The basic series of income shares of individuals, from 1991 to 2011, computed from the Census/by-census micro-data, is presented in Table 3.1. As the table illustrates, income inequality in Hong Kong has been at a very high level since 1991, and it had been slightly increasing among individuals over the past two decades. In each year, the top quintile individuals in Hong Kong had captured more than half of the aggregate income. This is not surprising considering that in other developed countries, such as the United States, the aggregate income received by the top quintile households has been above 50 percent of total income for most recent years (United States Census Bureau 2016). Moreover, in Hong Kong the share of aggregate income received by the top fifth has risen gradually from 51.8% in 1991 to 55.9% in 2011; that marks an 8% increase over the past twenty years. The shares of aggregate income received by the top 10, 5 and 1 percent of individuals had also risen slightly. Another clear pattern is that the income shares of the bottom three quintiles had declined over these years. For instance, the share of income received by the bottom fifth had decreased by 16% from 1991 to 2011. The story is slightly different for the fourth quintile as the share of income received by that group had not changed much over these years. Overall, more than half of aggregate income has been captured by individuals at the top of the income distribution since 1991. Table 3.1 also suggests that over the past two decades, rich people in Hong Kong have gained more wealth, while, the individuals at the bottom of the income distribution have received the same or lower income shares [4].

[4] The results are similar if I assume the top income earners have an average income of three times the threshold of the open-ended category. If an income of four times the threshold has been assigned to the top income earners, then the aggregate income received by the top fifth would be more than 60 percent in 2011, which is not common in reality. See Appendix Table A1 and A2. Therefore, I stick with an average income of two times the threshold.

Table 3.1: Income Shares of Individuals from All Employment in Hong Kong, 1991-2011 (%)

year	Quintiles					Bottom 10%	Top 10%	Top 5%	Top 1%
	Q1	Q2	Q3	Q4	Q5				
1991	5.0	10.3	13.8	19.0	51.8	1.3	37.8	27.5	12.5
1996	5.0	9.7	13.0	18.6	53.8	1.7	39.8	29.4	13.7
2001	4.6	9.1	12.9	19.5	53.9	1.6	39.0	27.9	12.3
2006	4.5	8.9	12.7	19.4	54.5	1.6	39.3	27.9	12.2
2011	4.2	8.7	12.2	19.1	55.9	1.5	40.5	28.9	13.1

Source: The Census and Statistics Department of Hong Kong, 1991-2011, compiled

The result is similar if household-level data is used. The statistics are presented in Table 3.2. The shares of aggregate income received by the bottom three quintiles had declined over time. For example, the income share of the bottom fifth had declined more than 13% from 1991 to 2011. This implies that individuals at the bottom of the income distribution had stayed at a disadvantage situation. The share of aggregate income received by the fourth quintile remained stable over the whole period. For the top fifth, however, we can notice a slight increase in the share of aggregate income from 52.1% in 1991 to 53.7% in 2011. Such increase in the income share also occurred to the top 10 and top 5 percent households, but not the top 1 percent. Loosely speaking, the results presented in Table 3.2 are consistent with those in Table 3.1 that earnings gap between rich and poor households has been big since 1991. And the gap had widened slightly over the whole period. The households at the bottom of the income distribution were doing worse over the whole period, while the rich households, such as the top 10 percent, had experienced a slight gain in their incomes.

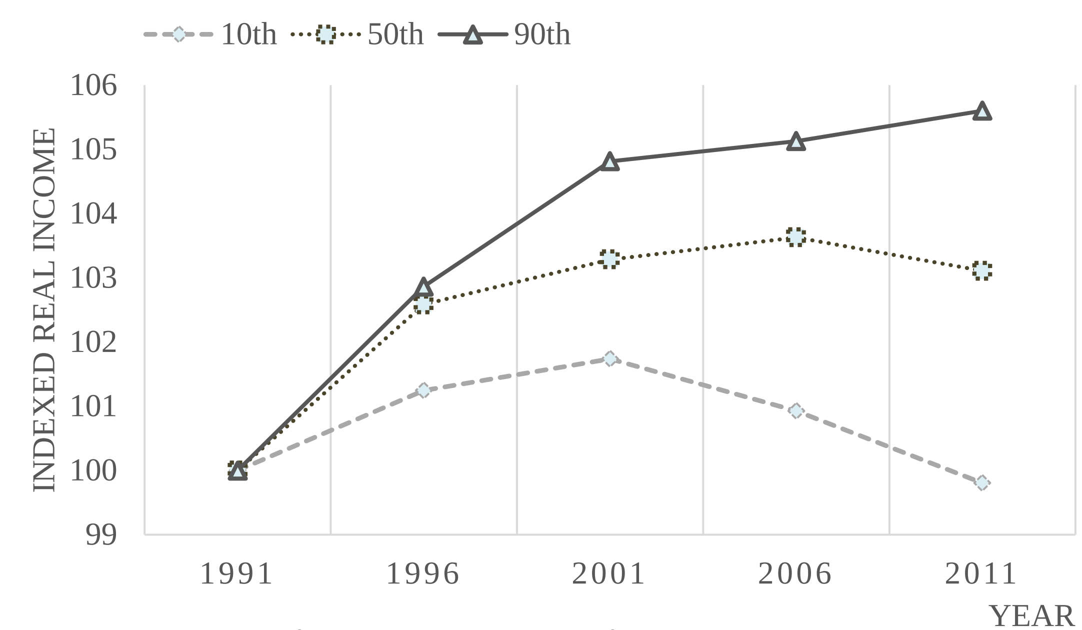
Table 3.2: Income Shares of Economically Active Households in Hong Kong, 1991-2011 (%)

year	Quintiles					Bottom 10%	Top 10%	Top 5%	Top 1%
	Q1	Q2	Q3	Q4	Q5				
1991	5.3	9.2	13.4	20.0	52.1	2.0	37.1	26.3	11.7
1996	5.1	9.1	13.5	20.2	52.3	1.9	37.3	26.5	10.5
2001	5.1	9.2	13.5	20.2	52.0	1.9	36.8	25.9	9.3
2006	4.8	8.9	13.4	20.2	52.8	1.8	37.5	26.3	9.6
2011	4.6	8.6	13.1	20.0	53.7	1.8	38.3	27.0	7.9

Source: The Census and Statistics Department of Hong Kong, 1991-2011, compiled

3.2.2 Income Distribution

Figure 3.1 graphs the 10^{th}, 50^{th}, and 90^{th} percentiles of the earnings distribution of all individuals in Hong Kong from 1991 to 2011. I indexed the earnings for the three groups to an average of 100 in 1991. As the figure shows, there is a distinct difference between the 10^{th} and the 90^{th} percentiles. For the 10^{th} percentile, income rose from 1991 to 2001 by about 2% and then fell sharply back to the 1991 level. Over the whole period, income at the 10^{th} percentile had remained the same. In contrast, income for individuals at the 90^{th} percentile rose about 6 percent from 1991 to 2011. Median income increased moderately from 1991 through 2006, then declined slightly, back to the level in 2001. Overall, median income had increased about 3 percent over the whole period. Figure 3.1 clearly shows that the earnings gap between the rich and the poor in Hong Kong was widening slightly with rich people gaining more wealth.

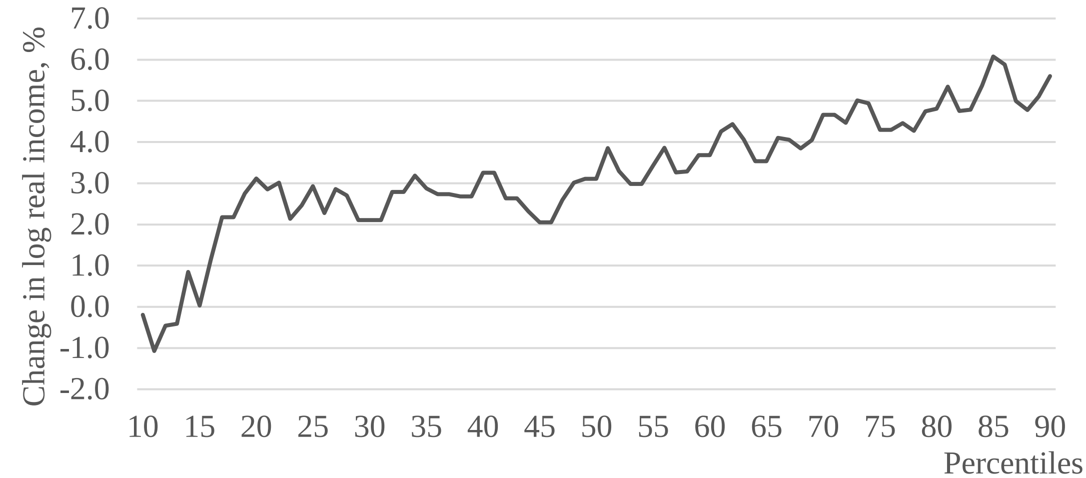


Source: Department of Census and Statistics of Hong Kong

Figure 3.1: Indexed Real Monthly Income of All Individuals in Hong Kong by Percentile, 1991-2011

Figure 3.2 shows the percentage change in real monthly income by income percentile from 1991 to 2011. An upward trend in the log real income change is present, showing evidence of rising income inequality over the period from 1991 to 2011 in Hong Kong. Specifically, the change in log real income is basically a linear function of the percentiles. As the figure shows, the divergence becomes more dramatic towards the upper percentiles of the income distribution. For the very bottom percentiles, such as the 10th percentile, individuals had experienced a loss in their income level, while individuals at the very top percentile, i.e. the 90th, had gained about 5.5% in their income over the whole period. This implies that the least skilled workers (proxied by the 10th percentile) had been in a disadvantaged position compared with the most skilled workers (proxied by the 90th percentile). Figure 3.2

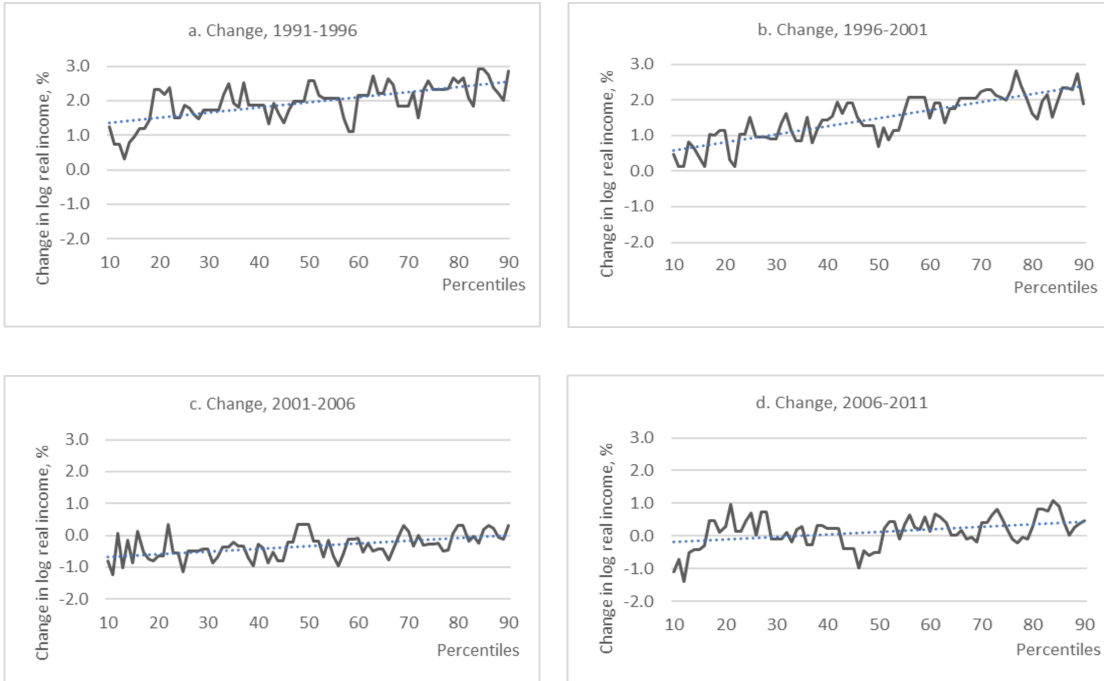
supports the idea that the income level of individuals at the top has been rising while the income level of individuals at the bottom has been falling in Hong Kong, which widens the income gap over the whole period.



Source: Department of Census and Statistics of Hong Kong

Figure 3.2: Change in log real monthly income by percentiles in Hong Kong, 1991-2011

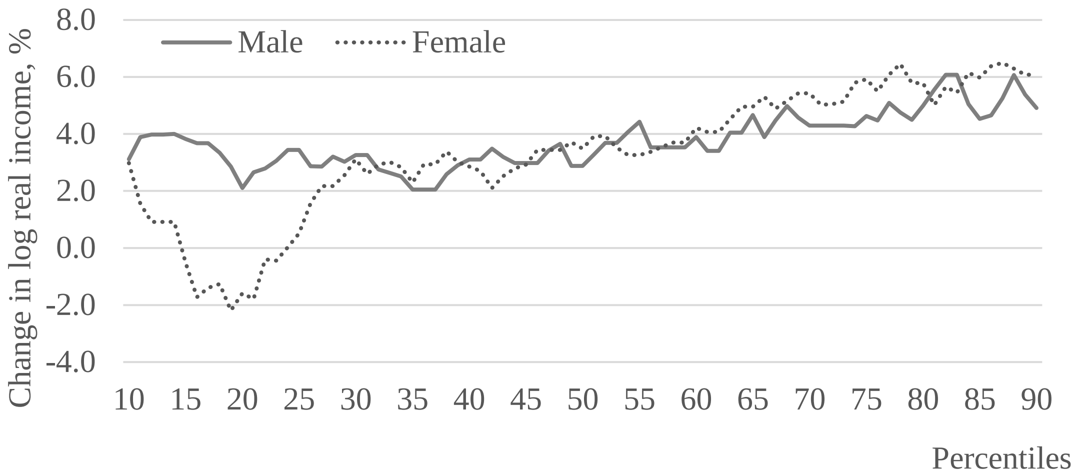
The four panels in Figure 3.3 break down the change in log real income from 1991 to 2011 into four sub-periods: 1991-1996, 1996-2001, 2001-2006 and 2006-2011. Also shown in Figure 3.3 is that the changes in real income were stable in all periods as the trends of the changes are relatively flat. Notice that the magnitude of the change in log income across percentiles is similar in each time period, thus income inequality did not change much in each time period. Therefore, I concentrate on the trend in the changes across percentiles in each sub-period. From 1991 to 1996 (Panel a), changes in log income across percentiles have a slight upward slope, indicating earnings diverged slightly across percentiles in this period. The upward trend in Panel b is more obvious, especially for the upper tail. This implies that inequality increased between 1996 and 2001. The increase is relatively small, though: the overall change in real income for individuals below the 30^{th} percentile was about 1 percent, in contrast it more than doubled on average for individuals above the 70^{th} percentile. Between 2001 and 2006, most individuals experienced a decline in their income levels, but the change was similar across the distribution. Panel d also shows no trend in the changes in log income, meaning income disparity did not change much over these two periods. Overall, most of the increase in income disparity occurred during the period of 1991 to 2001. Individuals at the upper percentiles experienced a gain in income, while individuals at the lower percentiles, on average, were at a disadvantage.



Source: Department of Census and Statistics of Hong Kong

Figure 3.3: Changes in Relative Income by Percentiles in Hong Kong, 1991-2011

I also broke the changes in the overall income distribution into changes within groups and changes between groups. Here I split the individuals into two groups: males and females. Figure 3.4 shows the log income changes by percentile separately for males and females. The figure shows no significant income differential between these two groups except for the bottom percentiles. At certain percentiles, as we can see, the changes in log real income for both males and females are the same. However, for some upper percentiles, the change in females was even greater than that of males.

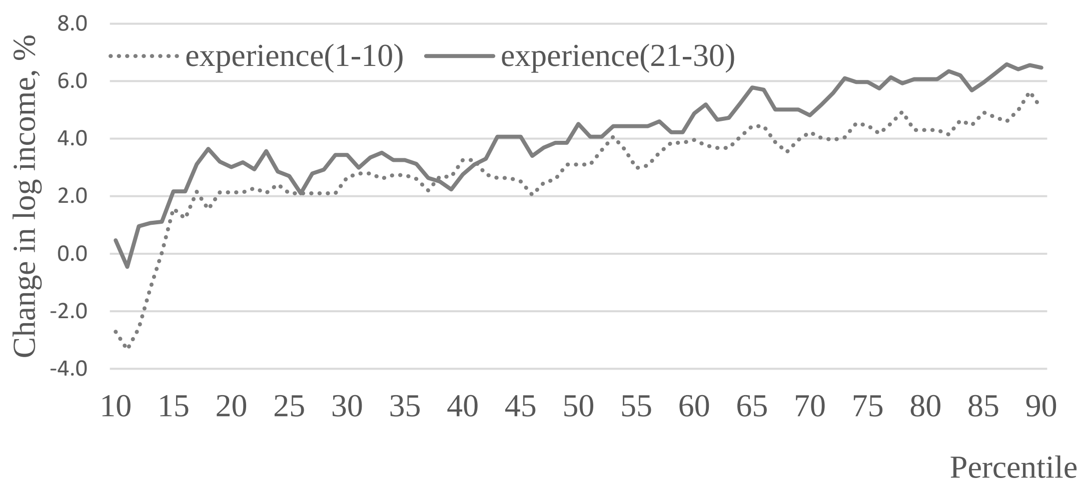


Source: Department of Census and Statistics of Hong Kong

Figure 3.4: Change in Log Real Income by Gender and Percentiles in Hong Kong, 1991-2011

Within-group differentials might be of interest, with regards to the females. As Figure 3.4 shows, the percentage change in log real income for males grew moderately towards the upper percentiles. This means that income disparity among males changed slightly over time. The percentage change in income for females ranged from -2 to 6, suggesting a significant upward trend in the changes across percentiles. Some of the low-paid females (i.e. 15th to 23rd percentiles) experienced a loss in their incomes, while the high-paid females experienced a gain. In general, this suggests that within-group differentials might be relatively important for women.

Figure 3.5 examines the income changes by percentile separately for individuals with 1-10 years of experience and individuals with 21-30 years of experience. As the figure illustrates, the change in log income for the more-experienced group was slightly bigger than that for the less-experienced group at all percentiles with a few exceptions. This implies that between-group differentials only changed minimally from 1991 to 2011. In addition, the changes in within-groups were modest as well over those years. Specifically, for the more-experienced group, the trend in the changes in log income across percentiles was relatively flat. Individuals at upper percentile gained slightly more than individuals at other percentiles. The story is similar for the least-experienced group. In summary, the increase in within-group inequality by experience group is modest, as is the between-group difference.



Source: Department of Census and Statistics of Hong Kong

Figure 3.5: Change in log real income by years of work experience by percentile in Hong Kong, 1991-2011

3.3 Components of Change in Income Inequality

As Figure 3.2 shows, income inequality increased modestly over the whole period from 1991 to 2011. In order to isolate the effect of each source on changes in income inequality, I apply the decomposition framework proposed by Juhn et al.

(1993). In their study, they assumed that residuals from the wage equation consist of two components: the distribution function of the wage equation residuals, $F_t(\cdot)$, and an individual's percentile in the residual distribution, θ_{it}, and Thus, the wage equation would be defined as

$$Y_{it} = X_{it}\beta_t + \varepsilon_{it} \tag{3.1}$$

where $\varepsilon_{it} = F_t^{-1}(\theta_{it}|X_{it})$. The key idea of their approach is to generate a counterfactual income distribution having subset of components held fixed. First, they held observable prices and residual distribution fixed, and then they allowed both observable prices to change over time.

Firstly, I run a pooled regression for the period of 1991 to 2011 and obtain the average prices of individual characteristics over the whole period, $\bar{\beta}$, and residuals from the pooled regression, which turns out to be normally distributed with mean zero and a small standard deviation. Then I run regressions for different years, obtaining the predicted value of each regression and the corresponding residuals. Lastly, each individual is assigned a counterfactual residual based on θ_{it} as well as the normal distribution over the complete sample.

The purpose of this decomposition method is to perform counterfactual analyses, specifically, reconstructing the income distribution by holding components fixed. Here, by holding return to skills and pooled residual distribution fixed, income distribution, Y_{it}^1, would be generated as

$$Y_{it}^1 = X_{it}\bar{\beta} + \bar{F}^{-1}(\theta_{it}|X_{it}) \tag{3.2}$$

Once I relax the constraints, allowing both return to skills and observable characteristics to vary through time, income distribution, Y_{it}^2, would be generated as

$$Y_{it}^2 = X_{it}\beta_t + \bar{F}^{-1}(\theta_{it}|X_{it}) \tag{3.3}$$

And finally, if I allow all these three sources to change through time, I would obtain

$$Y_{it}^{3} = X_{it}\beta_t + F_t^{-1}(\theta_{it}|X_{it}) \tag{3.4}$$

where Y_{it}^{3} is exactly the same as the observed income, Y_{it}. Once the distributions of Y_{it}^{1}, Y_{it}^{2}, and Y_{it}^{3} of each year are obtained, the over-time changes in inequality in the Y_{it}^{1} distribution would be attributed to changes in observable characteristics. Any additional changes in inequality in Y_{it}^{2} would be attributed to changes in return to skills, and finally any additional changes in inequality for Y_{it}^{3} would be attributed to changes in the distribution of unobserved quantities and prices (i.e., the residual). I also perform analyses for sub-periods 1991 to 2001, and 2001 to 2011.Table 3.3 quantifies the contributions of observed characteristics and return to skills, and the unobservables to the increase in the ninetieth-tenth, ninetieth-fiftieth, and fiftieth-tenth percentile log income differentials.

Table 3.3: Observable and Unobservable Components of Changes in Inequality in Hong Kong

Differential	Total change (1)	Observed Quantities (2)	Observed Prices (3)	Unobserved Price And Quantities (3)
		A. 1991-2011		
90/10	0.094	0.028	0.044	0.022
90/50	0.028	0.003	0.017	0.009
50/10	0.057	0.022	0.023	0.011
		B. 1991-2001		
90/10	0.058	0.023	0.025	0.010
90/50	0.018	0.002	0.010	0.005
50/10	0.035	0.019	0.012	0.004
		C. 2001-2011		
90/10	0.036	0.010	0.019	0.007
90/50	0.011	0.001	0.008	0.002
50/10	0.022	0.007	0.009	0.005

Source: The Census and Statistics Department of Hong Kong, 1991-2011, compiled

Panel A refers to the change over the whole period. The 90^{th}-10^{th} earnings differential increased 9.4 percentage points, and most of the change is concentrated in the lower half (0.057). Changes in observed characteristics account for around 10% of the rise in the 90^{th}-50^{th} earnings differential, but account for approximately 30% of the increase in the 90^{th}-10^{th} earnings differential, and 40% between the 50^{th} and 10^{th}. Changes in the return to skills explain about 40% of the increase in the 50^{th}-10^{th} earnings differential, and more than 60% of the rise in the 90^{th}-50^{th} percentile earnings differential. The unobserved components account for about 20 to 30 percent of the increase in inequality. In other words, roughly 70 to 80 percent of the increase in income inequality could be explained by observed components. Over such period, it is important to notice that the change in observed skill price has the biggest contribution to the increase in income inequality.

Panel B presents the result for the period from 1991 to 2001. The changes in observables account for about 90 percent of the rise in the 50^{th}-10^{th} earnings differential. The changes in observed return to skill prices play a very important role in explaining the ninetieth-tenth and ninetieth-fiftieth percentage differentials, while changes in observed quantities are more important in explaining the changes in the fiftieth-tenth percentile differential.

Panel C shows a similar story as Panels A and B as roughly 80 percent of the changes in income inequality could be explained by the observables. However, the changes in observed return to skill are more important in explaining changes in percentage differentials. For example, more than 70 percent of the ninetieth-fiftieth percentage differential could be accounted by the changes in the observed skill prices.

I also conduct a robustness check on the contributions of each component to the changes in overall inequality by assuming the top income earners have an average income of three times the threshold of the open-ended income category rather than two times. The results presented in Appendix Table A5 are similar to those in Table 3.3. From 1991 to 2011, the ninetieth-tenth ratio increased 9.4 percentage points. A large portion of the changes in overall inequality could be explained by the observables, especially the changes in the return to skills. For example, the changes in the observed skill price can account for about 57 percent of the changes in the 90-50 earnings differential from 1991 to 2011, and more than 80 percent of that from 2001 to 2011. In summary, approximately 70 to 80 percent of the change in income inequality could be explained by the observables, compared to only about 20 to 30 percent of the changes in income inequality explained by the unobservables.

The pooled and separate regressions results are presented in Appendix Table A3. All the parameters are significant at 1 percent level. Columns 2-4 refer to the whole period from 1991 to 2011. Over this period, the return to education in 2011 (0.135) is about 4 percentage points higher than in 1991 (0.096). The trend in the changes of return to education is like that found in the U.S. (Juhn et al. 1993). The change in the return to education over the period 1991-2001 is close to that of the period 2001-2011. This implies that the return to education in Hong Kong increased gradually over the past two decades. On the other hand, the return to experience increased only 1 percentage point from 0.042 in 1991 to 0.053 in 2011. Assigning top income earners a different average income level results in a similar conclusion. These results are shown in Table A4.

The results from Appendix Tables A3 and A4 imply that the return to skills in Hong Kong has risen over time, and this increase contributes to the change in earnings differentials in Hong Kong. In order to address the rise in the return to skills, we might need to investigate the changes in the demand for skills in Hong Kong. Over the past two decades, the demand had shifted from less-skilled to more-skilled workers as the economy restructured itself in Hong Kong. Hong Kong is located on China's south coast, and borders the city of Shenzhen in Guangdong Province to the north over the Sham Chun River. Following the opening-up of mainland China in 1978, also referred as economic reform, Hong Kong manufacturers took advantage of the very low labor and land costs in South China and moved their labor-intensive operations across the border into South China (Lam and Liu 2002). Table 3.4 shows the trend of employment by industry in Hong Kong over the past two decades.

Table 3.4: Employed Persons by Industry in Hong Kong, 1991-2011 (numbers in thousands)

	1991	2001	2011
Manufacturing	717 (26.0)	325 (10.0)	132.9 (3.7)
Construction	224.9 (8.2)	288.7 (8.9)	277 (7.8)
Wholesale, retail and import/export trades, restaurants and hotels	732.1 (26.6)	981 (30.2)	1,116.7 (31.2)
Transport, storage and communications	273.6 (9.9)	352.9 (10.9)	434.2 (12.1)
Financing, insurance, real estate and business services	229.1 (8.3)	482 (14.8)	676 (18.9)
Community, social and personal services	536.1 (19.5)	800.1 (24.6)	915.4 (25.6)
Other	40.9	23.1	24.1

Note: Numbers in parentheses are percentages.
Source: Figures are compiled from Hong Kong Annual Digest of Statistics, 1992-2012

As the table illustrates, employment has shifted from manufacturing toward the service sector and demand for labor shirts from the less-skilled toward the more-skilled. It is easy to notice that the number of employed persons in the manufacturing sector had declined dramatically, from 717,000 in 1991 to only 132,900 in 2011. As a percentage of the total employment, it dropped from 26.04% to only 3.72%. This suggests that fewer people in Hong Kong were employed in manufacturing in 2011 compared with two decades ago. In contrast, more and more people were employed in the service sector such as financing service, communications, etc. in 2011. We can also see the number of employed persons engaged in the trade sector had increased steadily. This is mainly because although products are manufactured in mainland

China, they are re-exported through Hong Kong, which stimulates a fast growth in the trade sector. Clearly, the economy of Hong Kong restructures itself rapidly to become service-oriented, requiring a big amount of skilled workers. The demand shift from low-skilled workers to high-skilled workers has contributed to the rising skill prices, which hence contributes to the widening earnings gap in Hong Kong.

Table 3.5: Distribution of Population by Educational Attainment in Hong Kong (%)

Educational Attainment	1991	1996	2001	2006	2011
Primary and below	28.3	21.1	17.4	13.9	11.5
Lower Secondary	21.0	20.3	19.7	19.0	17.8
Upper Secondary	36.6	38.3	37.5	37.1	35.5
Post-secondary	14.1	20.3	25.3	30.0	35.3

Source: Figures are compiled from Hong Kong Census/by-Census of 1991-2011

Meanwhile, the changes in the observed quantities, such as education and experience, are powerful at explaining the changes in income inequality based on results from Table 3.3. Over the past two decades, the educational attainments of working-age people in Hong Kong had changed significantly. Table 3.5 shows the distribution of population by educational attainment. The number of people with very little education (i.e. primary and below), as a percentage of the working-age population, had declined dramatically. In 1991, 28.3 percent of the working-age population never received secondary education. By contrast in 2011, only 11.5 percent of working-age population received very little education. On the other end of spectrum, the proportion of Hong Kong people with a higher level of education (i.e. post-secondary) increased from 14.1% in 1991 to 35.3% in 2011. Such an increase in education level accounts for a portion of the changes in income inequality. My findings, therefore, are that most of the changes in income inequality in Hong Kong are due to the changes in observables, specifically, the increase in education level and the rise in the return to skills.

3.4 Residual inequality

Although evidence has shown that observable characteristics including quantities, such as education and experience, and return to skills, account for part of the increase in the overall wage inequality, a large portion of the changes in overall inequality cannot be explained by those observable characteristics (Juhn et al. 1993; Lemieux 2006; Xing and Li 2012). Moreover, researchers have found that unobservables are very powerful in explaining the growth in overall wage inequality in the United States (Juhn et al. 1993). This implies that most of the changes in the overall inequality are within groups, rather than between groups. The results found in Figure 4 and Figure 5 are consistent with such idea. However, I find only 20 to 30 percent of the changes in the overall inequality could be explained by the unobservables. Still, it is necessary to examine the trend in the within-group inequality and investigate its underlying sources. Lemieux (2006) claimed that one good explanation to the rising residual wage inequality is the return to unobserved skills, and another reason could be the increasing dispersion in unobserved skills. In many studies, researchers have found the importance of the composition effect in explaining the residual inequality (Lemieux 2006; Xing and Li 2012). Thus in this study, I concentrate more on the impact of the composition effect on residual inequality.

The method for studying residual or within-group inequality and its determinants is similar to that of the study of overall inequality. Specifically, in both studies, the first step is to decompose the change in inequality and the second is to conduct a counterfactual analysis by holding some components fixed. Within-group variance is a good measurement of residual inequality, and it has been used in many of the residual inequality studies (Lemieux 2006; Xing and Li 2012). Juhn et al (1993) assumed that the residual consists of the unobserved skills and their prices. Together with Chay and Lee (2000), in which measurement error is allowed, the residual from a wage regression could be written as:

$$\varepsilon_{it} = p_t e_{it} + v_{it} \tag{3.5}$$

where ε_{it} is the residual from a Mincer-type wage regression, e_{it} is unobserved skills, p_t is the return to unobserved skills, and v_{it} is measurement error. This idea had been taken by many researchers (Lemieux 2006; Xing and Li 2012). Therefore, the residual variance is defined as:

$$Var(\varepsilon_{it}) = p_t^2 Var(e_{it}) + Var(v_{it}) \tag{3.6}$$

To account for the composition effect, Lemieux (2006) proposed a standard variance decomposition formula. He divided the individuals by education and experience into *j* groups, where *j* is a finite number. Thus, the unconditional variance of unobserved skills, $Var(e_{it})$, then would be connected to the conditional variance, σ_{jt}^2, shown as:

$$Var(e_{it}) = \sum_j \theta_{jt}\sigma_{jt}^2 \tag{3.7}$$

where θ_{jt} is the share of workers in experience-education group j at time t, and $\sigma_{jt}^2 = Var(e_{it}|x_{it} \in j)$. Additionally, the conditional variance of unobserved skills is related to the conditional variance in wages, V_{jt}, by the following equation:

$$V_{jt} = p_t^2 \sigma_{jt}^2 \tag{3.8}$$

The unobserved skills distribution among individuals within each group is assumed to be stable over time (Chay and Lee 2000). That is to say, $\sigma_{jt}^2 = \sigma_j^2$ for all time periods t. By doing so, I can examine the magnitude of the composition effect and its influence on residual inequality. In the absence of v_{it}, the residual variance, $Var(\varepsilon_{it})$, could be described as follows:

$$Var(\varepsilon_{it}) = p_t^2 \sum_j \theta_{jt}\sigma_j^2 = \sum_j \theta_{jt}V_{jt} \tag{3.9}$$

According to Lemieux (2006), the changes in the residual variance between years s and t could be decomposed into two components as follows:

$$\begin{aligned} V_t - V_s &= \sum_j \left(\theta_{jt}V_{jt} - \theta_{js}V_{js}\right) \\ &= \sum_j \theta_{js}\left(V_{jt} - V_{js}\right) + \sum_j V_{jt}\left(\theta_{jt} - \theta_{js}\right) \end{aligned} \tag{3.10}$$

The first term on the right-hand side of Equation 3.10 is a weighted average of changes in the within-group variance, which can be thought of as the changes in the counterfactual variance holding the distribution of unobserved skills fixed at the base period level, θ_{js}, by assumption. Thus, θ_{js} could be treated as the counterfactual weight. The composition effect, captured by the second term, can be easily computed by taking the difference between the changes in the overall residual variance and the changes in the counterfactual variance. Moreover, I can examine the contribution of the composition effect to the changes in the overall residual variance.

3.4.1 Trends in Within-Group Variances

In this study, I divide individuals into 20 skill groups on the basis of 5 education categories and 4 experience categories [5]. Table 3.6 shows the within-group variance for each experience-education group at the beginning year 1991 and end year 2011. The residual of each group is shown in column 1 for year 1991, and in column 2 for year 2011. The change in the within-group variance is reported in column 3.

[5] Five education categories: high-school dropouts, high-school graduates, some college, college graduates, and college postgraduates. Four experience categories: less than 10 years, between 10 and 20 years, between 20 and 30 years, and more than 30 years of potential experience.

Table 3.6: Within-Group Variance of Income by Experience-Education Cell in Hong Kong, 1991 and 2011

	within-group variance			work-force share		
	1991	2011	Change	1991	2011	Change
	(1)	(2)	(3)	(4)	(5)	(6)
A. *by education and experience*						
High-school dropouts:						
exp<=10	0.1492	0.2235	0.0744*	0.1825	0.0579	-0.1246
10<exp<=20	0.2416	0.2173	-0.0244*	0.2188	0.1092	-0.1096
20<exp<=30	0.3013	0.3394	0.0381*	0.1852	0.1439	-0.0413
30<exp	0.2827	0.3614	0.0788*	0.2104	0.2647	0.0543
High-school graduates:						
exp<=10	0.2035	0.2837	0.0802*	0.0239	0.0101	-0.0137
10<exp<=20	0.3814	0.2375	-0.1438*	0.0201	0.0104	-0.0097
20<exp<=30	0.6193	0.4109	-0.2084*	0.0095	0.0105	0.0010
30<exp	0.7885	0.5569	-0.2316*	0.0045	0.0100	0.0055
Some college:						
exp<=10	0.2252	0.3695	0.1444*	0.0294	0.0469	0.0174
10<exp<=20	0.3562	0.3179	-0.0383*	0.0145	0.0315	0.0170
20<exp<=30	0.4786	0.5616	0.0830*	0.0072	0.0249	0.0177
30<exp	0.6142	0.7346	0.1204*	0.0046	0.0157	0.0111
College graduates:						
exp<=10	0.4289	0.3562	-0.0727*	0.0368	0.0842	0.0474
10<exp<=20	0.6905	0.6013	-0.0892*	0.0253	0.0603	0.0350
20<exp<=30	0.9803	0.6985	-0.2818*	0.0131	0.0376	0.0245
30<exp	0.9664	0.8785	-0.0879	0.0082	0.0134	0.0052

Table 3.6 continued.

College postgraduates:						
exp<=10	0.3398	0.3537	0.0139	0.0026	0.0248	0.0222
10<exp<=20	0.5586	0.4978	-0.0608	0.0025	0.0240	0.0215
20<exp<=30	0.5621	0.6000	0.0378	0.0007	0.0157	0.0150
30<exp	0.7271	0.9193	0.1923	0.0003	0.0042	0.0040
B. *weighted average (using alternative shares)*						
Actual shares	0.2922	0.3876	0.0953			
1991 shares	0.2922	0.3156	0.0233			
2011 shares	0.3782	0.3876	0.0093			

Note: “*” indicates that the change in the variance is significantly different from zero at the 95-percent confidence level.

Table 3.6 shows some clear patterns in the within-group inequality. To some extent, the within-group variance grows as a function of both education and experience. For example, at each education level as experience increases, within-group variance increases in both years with a few exceptions. High-school dropouts with potential experience less than 10 years have a variance of 0.1492, which is the lowest variance in 1991. By contrast, post-college graduates with potential experience of more than 30 years have a variance of 0.9193, the largest variance in 2011. This suggests that composition effects are likely to have significant impacts on the residual inequality as both education and experience increase over time.

Columns 4 and 5 show the share of each skill group in the work force in 1991 and 2011, respectively, while column 6 shows the change in the shares over time. The share declined significantly for individuals in groups with low within-group earnings disparity. On the contrary, the share rose for individuals with post-secondary education within each experience group. These results suggest that there has been a big change in the distribution of skills over time. Moreover, the correlation coefficient between column (2) (the within-group variance in 2011) and column (6) (the change in share) is about 0.40. This implies a big and positive composition effect according to Equation 3.10.

The lower panel of Table 3.6 shows the precise contribution of the composition effects to the residual inequality. The weighted average of the within-group variances, presented in the first row of the lower panel, is estimated when the actual shares in the corresponding year are used. As the table shows, the change in the residual variance between 1991 and 2011 is 0.0953. The second row shows that the change in the within-group variance is 0.0233 when the shares are held at the 1991 level. It implies that the within-group variance rises by 0.0233 over time when the year 2011 has a same distribution of unobserved skills as the year 1991. This implies a significant composition effect. If shares are held at the 2011 level, the change in the residual variance would be 0.0093, suggesting an even bigger composition effect.

For sensitivity analysis, I also divide individuals into 16 skill groups based on 4 experience categories and e education categories as well (primary and below, lower secondary, upper secondary and post-secondary). The results are presented in Appendix Table A6. Not surprisingly, the results are similar to those found in Table 3.6. Specifically, the within-group variance grows as a function of education and experience. The correlation coefficient between the change in share and the within-group variance in 2011 is 0.536. All these findings are consistent with those from Table 3.6, in that they imply that the composition effect is quite important to the changes in the residual inequality. From the lower panel of Table 4A, the result suggests that around 75% of the growth in the within-group variance is due to the composition effect.

3.4.2 Changes in the Residual inequality: Reweighting Results

Although the result above shows strong evidence of composition effect and its big influence to the residual variance, it would be more robust to concentrate on each individual instead of 20 groups. That being said, we should focus more on the contribution of each individual to the residual variance. Therefore, the residual variance can be computed using the following formula:

$$V_t = \sum_i \omega_{it} \varepsilon_{it}^2 \tag{3.11}$$

where ω_{it} is the sample weight. It is safe to claim that the data being used here is randomized, and thus ω_{it} would just be the inverse of the number of observations.

Similarly, the counterfactual variance using individual-level data could be estimated as

$$V_t^* = \sum_i \omega_{it}^* \varepsilon_{it}^2 \tag{3.12}$$

The counterfactual weight, ω_{it}^*, makes the distribution of skills in year *t* the same as in the base year *s*. Once the counterfactual weight, ω_{it}^*, is obtained, it would be easy to estimate the composition effect. In general, when the skill distribution of 2011 is converted back to its 1991 level, less weight need to be put on individuals who are more educated and experienced. This is because over time the share of those individuals rises over time. Either a logit or probit model is useful if I need to reweight the individuals in the year 2011 holding the skill distribution at its 1991 level. Here, I use a logit model to estimate the counterfactual weight.

In order to reweight the individuals in year 2011, firstly, I pool these two years together, and create a dummy variable for the year 1991. Secondly, I run a logit model for this dummy variable on the same explanatory variables as before. The predicted probability that worker i is in year 1991, P_i, is then used to compute the counterfactual weight as $\omega_{it}^* = [(1 - P_i)/P_i]\omega_{it}$. Younger and less experienced workers are relatively more likely to be observed in 1991 than in 2011, implying a larger value of P_i and smaller value of $(1 - P_i)/P_i$. Therefore, these workers are "downweighted" when ω_{it} is replaced by ω_{it}^*. I also reweight the individuals in year 1991 by holding the skill distribution at the 2011 level. The dependent variable in the corresponding logit model would be the dummy variable for year 2011. Lastly, I choose the middle year, 2001, as the base year, to reweight the individuals in year 1991 and 2011 and check if the result is significantly different.

Figure 3.6 illustrates the actual residual variance from 1991 to 2011 and three counterfactual variance series holding the distribution of skills fixed at its 1991, 2011 and 2001 levels, respectively. The composition effects can be estimated by subtracting the counterfactual variances from the actual variance. As shown in the figure, from 1991 to 2011 the actual residual variance grows by 0.105. When the skill distribution is held constant at its 1991 level, the counterfactual variance grows by 0.070. In contrast, the counterfactual variance grows by 0.040 holding the distribution of skills at its 2001 or 2011 level. Figure 3.6 implies the composition effects contributes a lot to the growth in within-group inequality.

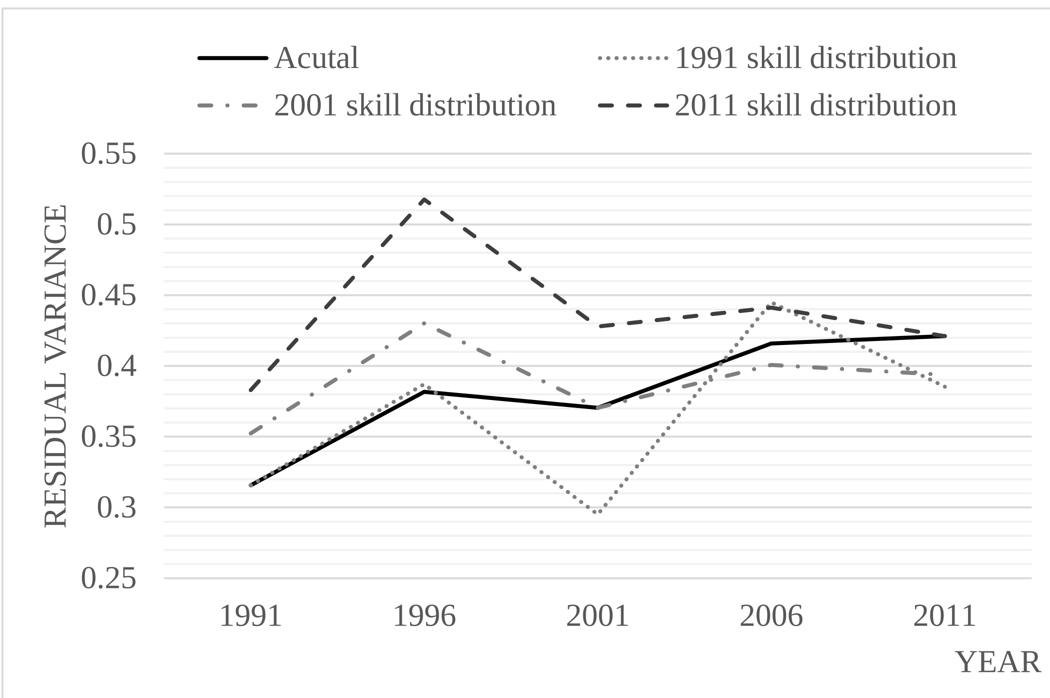


Figure 3.6: Actual and Counterfactual Residual Variance in Hong Kong, 1991-2011

Table 3.7 shows more details about the result, and it implies that the composition effects explain a large portion (more than 60 percent) of the growth in the within-group variance over the whole period by holding the distribution of skills at its either 2001 or 2011 level. Although the size of composition effect is less dramatic when the skill distribution is held at its 1991 level, the composition effects can still explain about 40 percent of the rise in the within-group variance.

Table 3.7: Composition Effects and Changes in the Residual Variance

	91-96	96-01	01-06	06-11	91-11
Actual Change	0.0661	-0.0112	0.0453	0.0053	0.1054
1991 skill distribution	0.0714	-0.0920	0.1498	-0.0596	0.0697
					[33.9%]
2001 skill distribution	0.0778	-0.0596	0.0302	-0.0069	0.0414
					[60.7%]
2011 skill distribution	0.1347	-0.0898	0.0133	-0.0200	0.0382
					[63.8%]

Note: number in square brackets represents the percentage of change in residual variance over the whole period explained by the composition effects.

In addition, this reweighting approach can be used to compute counterfactual measures of residual wage dispersion, such as the 90-10 residual gaps. Here I present a robustness check using alternative measures of wage dispersion. Figure 3.7 shows the actual and counterfactual 90-10 and 50-10 residual gaps holding skills at its 2001 level. These results are similar to those for the residual variance in which the composition effects account for a lot of the growth in the residual inequality.

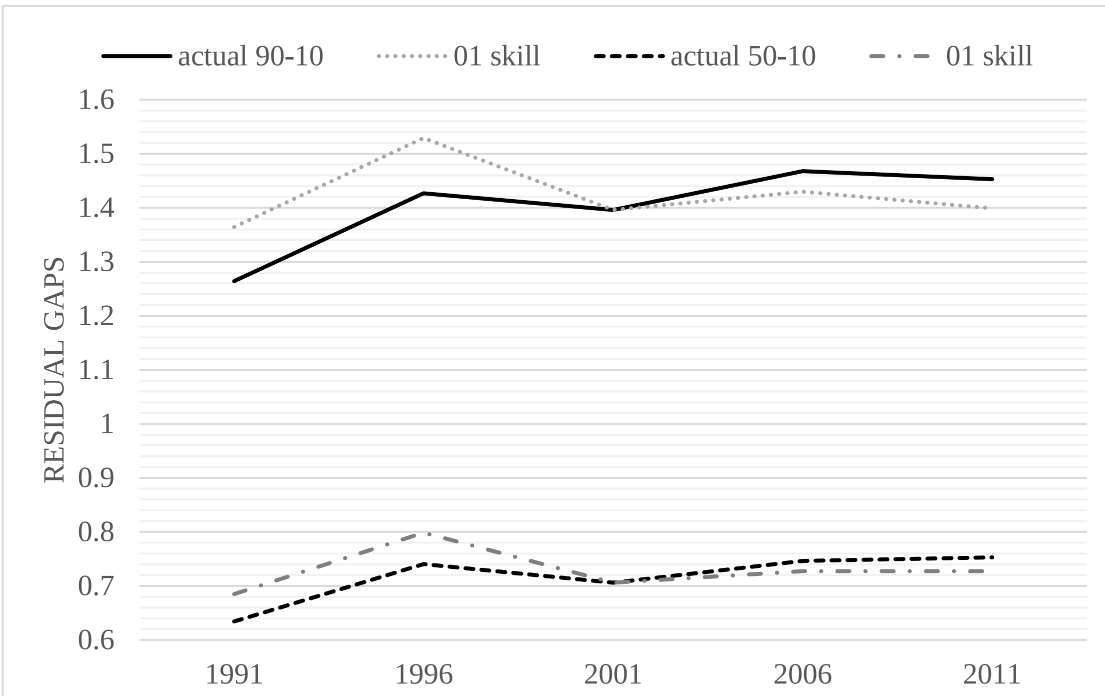


Figure 3.7: Residual 90-10 and 50-10 Wage Gaps in Hong Kong, holding distribution of skills at their 2001 level

Chapter 4

GENDER EARNINGS INEQUALITY IN HONG KONG: 1991-2011

4.1 Introduction

Through the significant progresses made by women in the labor market, including narrowing down the labor force participation rate gap between males and females and entering prestigious occupations dominated by men, the gender earnings differential in Hong Kong has diminished over a 25-year period since 1976, despite slight fluctuations (F. M. Cheung and Holroyd 2009). Specifically, women on average earned 35% less than men in 1976 (Mak and Chung 1997). The gender earnings differential declined from 1976 to 1986, and then it increased in the next five years (Westwood, Ngo, and Leung 1997). In 1991, female workers' earnings were 30% less than male workers' on average, and by 1996, they were only 16% less (Chung 1996; Sung, Zhang, and Chan 2001). Cheung and Holroyd (2009) studied the trend of earnings differential from 1991 to 2001 and found that the gap narrowed significantly over the whole period although it widened slightly from 1996 to 2001.

Researchers are interested in the determinants which narrow down the gender earnings gap. Several determinants have been discovered from different regions. Chung (1996) argued that the improvement of females' personal characteristics, particularly regarding human capital, had reduced the gender earnings gap from 1976 to 1991 in Hong Kong. In the United States, O'Neil and Polachek (1993) found that the convergence in measurable work-related characteristics such as schooling and work experience contributed a lot to the narrowing of the gender earnings gap. Other than education and experience, females' occupational upgrading and deunionization of males could also narrow down the gender earnings differential (Blau and Kahn 1997; Blau and Kahn 2006).

As mentioned above, researchers have conducted many studies on gender earnings differential till 2001 in Hong Kong, however, the most recent trend in the gender earnings gap in Hong Kong has not been studied yet. Hence, it is necessary to examine the trend of the gender earnings gap in the new era, and its underlying determinants. In this study, firstly I present the progress that women in Hong Kong have made in the labor market since 1991. Secondly, I examine the trend of the gender earnings gap through several perspectives, including mean earnings difference between males and females, gender earnings ratio, gender earnings gap by percentile, and earnings gap by experience group. In the empirical analysis, I first apply the Oaxaca-Blinder decomposition method to investigate the determinants of the gender earnings differential at the mean level. In addition, I apply the Recentered Influence Function (RIF) method to examine the gender earnings differential at different quantiles, and their underlying determinants.

This study makes two important contributions. Firstly, previous researchers had studied the gender earnings gap in Hong Kong till 2001, and found that most of the earnings differential could not be explained by the difference in individual characteristics (Lui and Suen 1994; F. M. Cheung and Holroyd 2009). By using census/by-census datasets from 1991 to 2011, my study will not only update the trend of the gender earnings gap in Hong Kong for the most recent years but also reexamine the importance of females' characteristics including years of schooling, work experience, and occupation to the gender earnings gap. Secondly, more than just concentrating on the mean level of earning by using the widely-used Oaxaca-Blinder method, this study also investigates the earnings gap at different earnings percentiles by using the Recentered Influence Function method, which allows me to address potential “sticky floor” and “glass ceiling” problems in Hong Kong.

The rest of the chapter is organized as follows: Section 2 presents labor market characteristics and earnings for men and women. Section 3 discusses the Oaxaca-Blinder technique. Section 4 discuss the Recentered Influence Function method with unconditional quantile and decomposition technique.

4.2 Descriptive Statistics

In this section, I examine the progress that women in Hong Kong made in the labor market from 1991 to 2011. Firstly, I examine the trend in the labor force participation rate for males and females in Hong Kong. Then I examine the trend in the gender earnings differential in several ways.

4.2.1 Labor Force Participation Rate

Figure 4.1 shows the pattern of labor force participation rate (hereafter, LFPR) for males and females in Hong Kong since 1991. The estimates are compiled from several Annual Digests of Statistics. Clearly, the male LFPR in Hong Kong declined monotonically from 1991 to 2011. In contrast, the female LFPR increased gradually from 47.8 percent in 1991 to 53.0 percent in 2011. Thus, the gap between males and females in LFPR narrowed over time. To some extent, women made progress in the labor market.

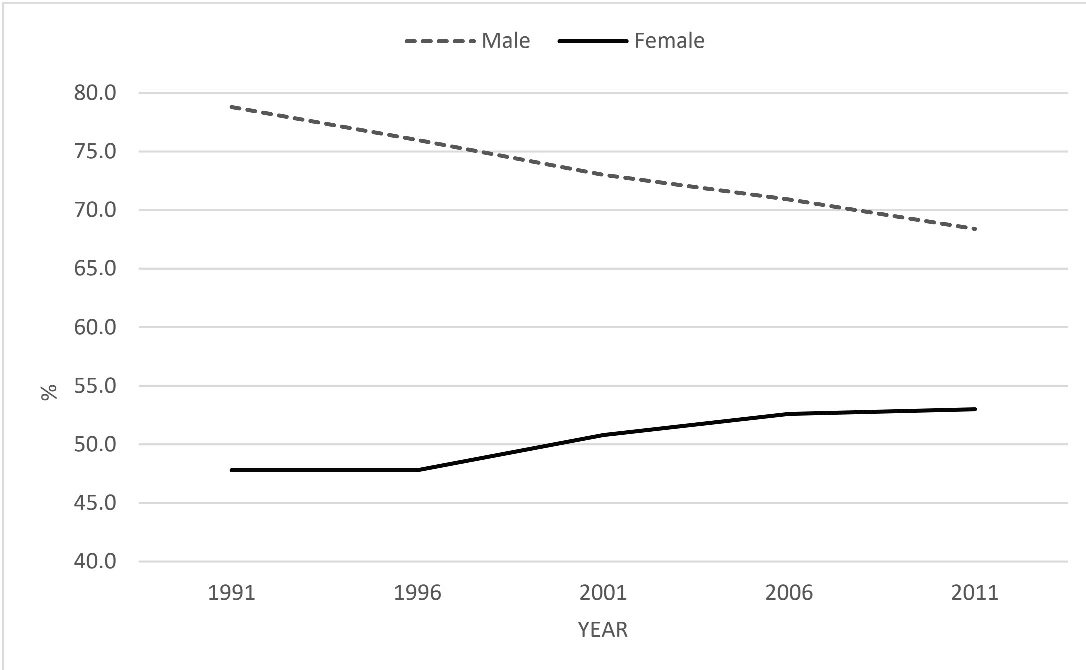


Figure 4.1: Labor Force Participation Rate for Males and Females in Hong Kong, 1991-2011

Table 4.1 presents some details about the LFPR among females by age group. Two points need to be noted. Firstly, LFPR declined substantially over time among those aged 15-24. This is mainly due to an increase in education enrollment rate. Specifically, only 56 girls aged 15 were enrolled in secondary schools in 1991. In contrast, 36,282 girls in the same age went to secondary school in 2011. Teenage girls took advantage of increased school places and more openness in parents’ attitudes towards sending their daughters to schools, and postponed their entry into the labor market (Mak and Chung 1997). Thus, the LFPR of that age group was driven down gradually by the educational expansion. Secondly, the LFPR for women aged 25-64 had increased over time, indicating more women had joined the labor market. Cheung and Holroyd (2009) claimed that the economic restructuring process in Hong Kong relocated many factories from Hong Kong to southern China and shifted economic activities toward the service sector, and thus more career opportunities in the service sector are open for females since the economic reform in 1978 in mainland China. Therefore, the continuous influx of women into the labor market can be attributed to the globalization and economic restructuring process (F. M. Cheung and Holroyd 2009). Additionally, rising real wage attracted more women to enter the job market.

Table 4.1: Labor Force Participation Rate among Females by Age Group in Hong Kong (%), 1991-2011

	1991	1996	2001	2006	2011
15-19	25.7	18.7	15.5	13.1	9.1
20-24	81.6	77.6	72.3	71.1	62.1
25-29	79.6	82.9	86.8	87.2	87.5
30-34	59.1	68.9	76.4	78.9	80.1
35-39	52.3	56.6	66.0	72.3	73.5
40-44	53.9	54.0	60.5	67.3	71.7
45-49	52.2	51.3	56.3	62.7	68.3
50-54	41.6	39.3	47.2	53.1	58.7
55-59	27.5	26.2	32.4	36.3	42.8
60-64	17.2	11.2	10.3	14.3	21.3
65 and over	6.4	2.6	1.9	1.8	2.3

Source: Hong Kong Annual Digest of Statistics, compiled

4.2.2 Gender Earnings Gap Facts

The narrowing of the gap between males and females in the LFPR does not imply a smaller gap in terms of earnings between males and females. Table 4.2 summarizes the overall trends for all economically active individuals aged 15 to 65 in Hong Kong from 1991 to 2011. Over the whole period, mean earnings had increased for both men and women, and such rise in earnings is slightly higher for men (37.2%)

than for women (30.0%). Note that the earnings distribution also widened for both men and women over time as the standard deviations for both groups had increased substantially. Overall inequality proxied by the standard deviation rose for women (0.219) more than for men (0.125). The percentile of the mean earnings of women in the distribution of men's earnings increased from 28.4 in 1991 to 36.3 in 2011, and this implies a smaller group earnings differential. Nevertheless, the over-time changes in both mean earnings difference and gender earnings ratio provide strong evidence of a widening gender earnings gap. For instance, the mean female-male earnings ratio fell from 71.1% in 1991 to 68.0% in 2001 and then it remained relatively stable in the following decade. The decline in the gender earnings ratio over the whole period suggests a slight divergence in earnings between males and females. The change in mean earnings difference tells the same story of a slight increase in earnings gap from 1991 to 2011. By assuming the top income earnings have income three times the threshold, I obtain similar results which are presented in Appendix Table B1.

Table 4.2: Overall of Earning Trends in Hong Kong, 1991-2011

	1991	1996	2001	2006	2011
Mean Log Male Earnings	9.298	9.456	9.629	9.584	9.614
	(0.689)	(0.741)	(0.762)	(0.793)	(0.814)
Mean Log Female Earnings	8.956	9.142	9.243	9.233	9.219
	(0.647)	(0.717)	(0.781)	(0.814)	(0.866)
Mean Difference	0.341	0.313	0.385	0.351	0.395
Gender Earnings Ratio	71.1	73.1	68.0	70.4	67.4
Position of Mean Female in the Male Distribution	28.4	33.5	29.9	32.5	36.3

Note: numbers in parentheses are standard deviations
Source: Census and By-census datasets, compiled

More than concentrating solely on the mean level of earnings, I examine the trend in earnings differential by deciles over time. Table 4.3 illustrates the gender earnings gap by each decile of the respective male and female earnings distributions for each year. In most years, the earnings gap was found to be larger at smaller deciles than other deciles. For instance, the earnings differential in 2011 for the 10^{th} percentile (0.671) and for the 20^{th} percentile (0.754) individuals was substantially bigger than other percentiles. Besides, I find that over time the trend in the earnings gap at the lower deciles differs substantially from the median or the upper deciles. Over the whole period, the earnings gap remained quite stable for the median, and it declined moderately for the 90^{th} percentile. In contrast, the gap for the first decile more than doubled from 0.330 log points to 0.671 log points in the same period. This means that women at lower percentiles experienced a much slower increase in earnings compared to men at the same positions. The wider divergence between female and male earnings among lower earnings positions is consistent with the theory of "sticky floor" effect [6]. By using 2006 by-census data, Ge et al (2011) found the existence of both the "sticky floor" effect and the "glass ceiling" effect in Hong Kong. Based on Table 4.3, the "glass ceiling" effect was presented in early years, but not in the later years.

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[6] The term "sticky floor" is used to describe a discriminatory employment pattern that keeps a certain group of people such as females at the bottom of the job scale. Thus, gender earnings gap tends to be higher in lower positions. Another term "glass ceiling" is used to describe an artificial discriminatory barrier which blocks the advancement of women or people of color who already hold good jobs, usually in middle management. Therefore, gender earnings gap tends to be higher in higher positions.

Table 4.3: The Gender Earnings Gap in Hong Kong by Distribution Percentile, 1991-2011

	Percentile								
	10	*20*	*30*	*40*	*50*	*60*	*70*	*80*	*90*
1991	0.330	0.288	0.334	0.300	0.307	0.336	0.288	0.288	0.357
1996	0.383	0.442	0.288	0.251	0.223	0.274	0.223	0.236	0.405
2001	0.492	0.598	0.449	0.288	0.288	0.388	0.325	0.223	0.288
2006	0.505	0.560	0.400	0.357	0.258	0.326	0.268	0.194	0.288
2011	0.671	0.754	0.416	0.318	0.300	0.288	0.288	0.318	0.316

Note: The gender earnings gap is the male earnings at a certain decile minus the female earnings at the same decile.

Figure 4.2 plots the changes in the gender earnings gap by selected percentiles from 1991 to 2011. Together with Table 4.3, I can see that from 1991 to 2011, the earnings differential between males and females at upper percentiles declined moderately. However, group earnings diverged at lower percentiles. Thus, the earnings divergence at lower positions, especially the bottom 25 percentiles, contributed a lot to the widening of the overall gender earnings gap from 1991 to 2011.

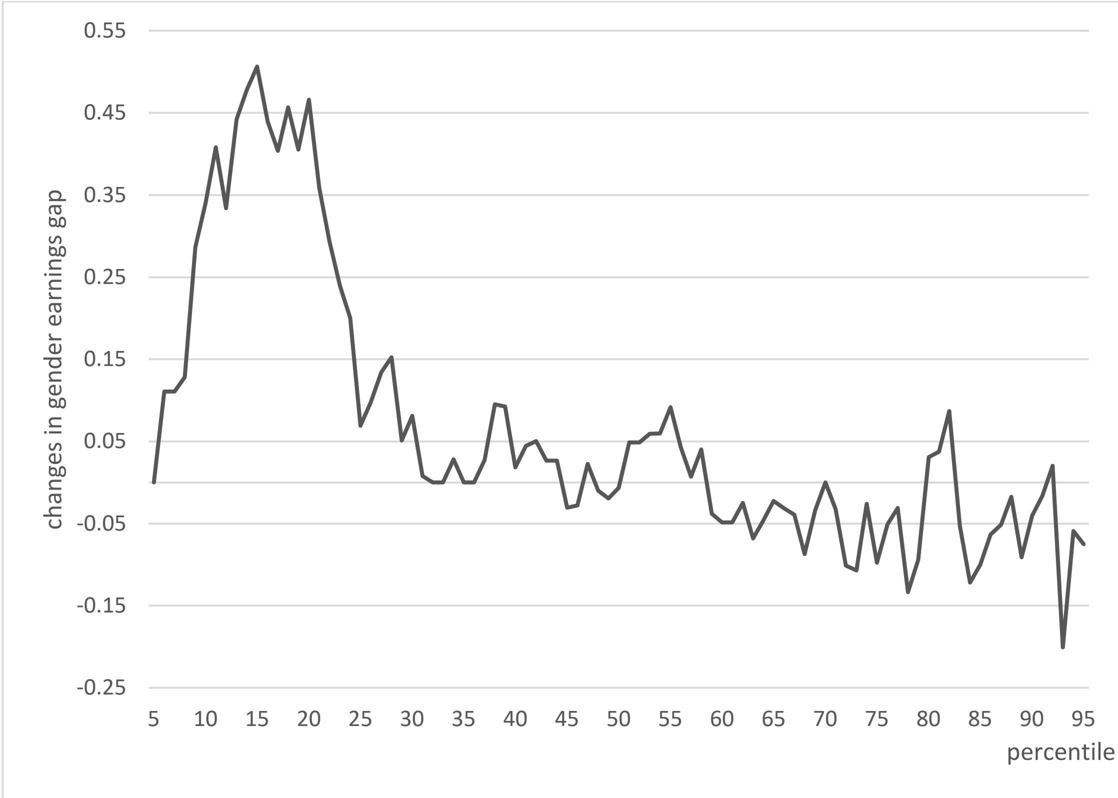

Figure 4.2: Changes in the Gender Earnings Gap by Percentile in Hong Kong, 1991-2011

Table 4.4 presents the female-male earnings differentials by potential experience level from 1991 to 2011. Over the whole period (comparison of the first and last columns), earnings diverged at lower levels of experience, while they converged at upper levels of experience. Put in another way, the earnings gap widened between women and men with less experience, while it narrowed for more-experienced groups. The pattern is similar for the period of 1991 to 1996. Earnings diverged substantially at every experience level from 1996 to 2001. It is almost the same pattern between 2006 and 2011 except the most-experienced group. Following cohorts down the diagonals, I see that earnings diverged among less-experienced groups while they converged among more-experienced groups. Therefore, most of the increase in the earnings differential (from 0.341 in 1991 to 0.395 percentage points in 2011) between females and males is concentrated on less-experienced groups. Notice that less-experienced individuals tend to be located at the lower percentiles of the earning distribution, thus the findings from this table are consistent with previous tables.

Table 4.4: Female-Male Earnings Differentials by Experience Level, 1991-2011

	1991	1996	2001	2006	2011
All experience levels	0.341	0.313	0.385	0.351	0.395
0-5	0.016	0.046	0.120	0.047	0.059
6-10	0.179	0.191	0.289	0.233	0.262
11-15	0.295	0.308	0.376	0.368	0.487
16-20	0.408	0.353	0.431	0.418	0.525
21-25	0.516	0.458	0.481	0.424	0.519
26-30	0.590	0.506	0.567	0.457	0.520
31-35	0.596	0.546	0.556	0.509	0.514
More than 35	0.514	0.441	0.496	0.464	0.458

Note: Standard errors for the "all experience levels" estimates are approximately 0.004 in each year. Standard errors for individual-experience level estimates range from 0.008 to 0.013.

4.3 Oaxaca-Blinder Decomposition Approach

The Oaxaca-Blinder decomposition method is one of the most popular approaches to study gender earnings disparity. The approach decomposes mean differences in log wages in linear regression models in a counterfactual manner. Thus, gender wage differentials are divided into a part that is "explained" by group differences in individual characteristics such as education and experience, and a part that is "unexplained" (Oaxaca 1973; Blinder 1973). Specifically, following a typical

Mincer-type wage equation, earnings variable is regressed on a set of explanatory factors for males and females separately. That is,

$$Y_i = X_i\beta + \varepsilon_i \tag{4.1}$$

where Y_i is the log earnings of individual i, and X_i is a set of individual characteristics, β is a vector of coefficients, and ε_i is a residual term assumed to be normally distributed with mean zero and constant variance. Thus, the difference between the two groups' means can be expressed as

$$\bar{Y}_m - \bar{Y}_f = \bar{X}_m\hat{\beta}_m - \bar{X}_f\hat{\beta}_f \tag{4.2}$$

where *m* = *male* and *f* = *female*. The next step is to add and subtract the term $\bar{X}_f\hat{\beta}_m$ ($\bar{X}_m\hat{\beta}_f, alternatively$) to the right side of the equation as follows:

$$\bar{Y}_m - \bar{Y}_f = (\bar{X}_m\hat{\beta}_m - \bar{X}_f\hat{\beta}_m) + (\bar{X}_f\hat{\beta}_m - \bar{X}_f\hat{\beta}_f) \tag{4.3}$$

The term $\bar{X}_f\hat{\beta}_m$ is treated as a counterfactual, representing the wage females would have earned under the males' wage structure. By rearranging terms in Equation 4.3, I obtain the following expression:

$$\bar{Y}_m - \bar{Y}_f = \left(\bar{X}_m - \bar{X}_f\right)\hat{\beta}_m + \bar{X}_f\left(\hat{\beta}_m - \hat{\beta}_f\right) \tag{4.4}$$

The first term on the right side of Equation 4.4 represents the "explained" portion of earnings difference or the composition effect. It measures the group wage difference due to covariate differences. The second term represents the "unexplained" portion of earnings differences. The coefficient estimates are presented in Appendix Table B2.

Table 4.5: Summary of Oaxaca-Blinder Decomposition Method Estimates in Hong Kong, 1991-2011

	1991	1996	2001	2006	2011
Panel A. Gender Earnings Differential					
Overall Gap	0.341	0.313	0.385	0.351	0.395
% Explained	33.19	39.53	44.86	46.05	42.44
Panel B. Contribution of Covariates Differences to Gender Earnings Gap					
Education	-0.014	-0.023	-0.016	-0.007	-0.004
	[(4.23)]	[(7.41)]	[(4.07)]	[(2.00)]	[(1.03)]
Experience	0.061	0.052	0.051	0.055	0.039
	[17.90]	[16.70]	[13.16]	[15.59]	[9.85]
Duration	0.005	0.000	0.006	0.003	-0.006
	[1.53]	[(0.11)]	[1.45]	[0.85]	[(1.52)]
Birth Place	0.002	0.030	0.036	0.013	0.016
	[0.68]	[9.49]	[9.22]	[3.78]	[4.06]
Occupation	0.059	0.065	0.097	0.098	0.123
	[17.30]	[20.84]	[25.10]	[27.83]	[31.09]

Note: Each main entry of this table represents the contribution of each characteristic to the overall gap. Its percentage is in brackets.

Table 4.5 (Table 4.5-1 with alternative measures) presents a summary of the Oaxaca-Blinder decomposition method estimates for Hong Kong since 1991. Panel A shows the trend in the gender earnings gap and the portion of the earnings gap being explained. As shown in Panel A, the gender earnings gap in Hong Kong widened slightly from 1991 to 2011. The portion of earnings differential explained by covariates differences grew at a decreasing rate from 1991 to 2006 and then declined slightly afterwards. Note that one third of earnings differentials is due to the difference in individual characteristics, leaving two thirds of the earnings differential unexplained in 1991. In contrast, covariates differences account for 42.44% of the gender earnings gap in 2011. Still, a big part of the gender earnings differential at the mean level could not be accounted for by covariates differences.

Table 4:5-1 Summary of Oaxaca-Blinder Decomposition Method Estimates in Hong Kong with Alternative Dependent Variable, 1991-2011

	1991	1996	2001	2006	2011
Panel A. Gender Earnings Differential					
Overall Gap	0.342	0.315	0.388	0.353	0.398
% Explained	33.32	39.65	44.98	46.03	42.19
Panel B. Contribution of Covariates Differences to Gender Earnings Gap					
Education	-0.015	-0.023	-0.016	-0.007	-0.004
	[(4.24)]	[(7.45)]	[(4.11)]	[(2.01)]	[(1.04)]
Experience	0.061	0.053	0.051	0.055	0.040
	[17.95]	[16.80]	[13.25]	[15.67]	[9.95]
Duration in Hong Kong	0.005	0.000	0.005	0.002	-0.007
	[1.48]	[-0.10]	[1.34]	[0.70]	[-1.82]
Birth Place	0.002	0.030	0.036	0.013	0.016
	[0.70]	[9.39]	[9.30]	[3.77]	[3.97]
Occupation	0.060	0.066	0.098	0.098	0.124
	[17.42]	[21.02]	[25.21]	[27.90]	[31.13]

Note: Each main entry of this table represents the contribution of each characteristic to the overall gap. Its percentage is in brackets.

Panel B of Table 4.5 shows the contribution of each individual characteristic to the overall earnings gap in each year. Several findings need to be pointed out [7]. Firstly, education has a negative effect on the gender earnings gap. In other words, education contributed to the narrowing of the gender earnings gap in each year, albeit modestly. Females on average had achieved more years of schooling than males in each year. This can be seen in Table 4.6. The difference in educational attainment between males and females in Hong Kong was larger in the first decade. This also

[7] An individual's duration in Hong Kong has little to no contribution to the gender earnings gap, and birth place contributes to the widening of gap, however, the effect is quite small.

corresponds to the larger negative magnitude of the earnings effects in the first decade illustrated by the coefficient estimate of education in Table 4.5.

Table 4.6: Descriptive Statistics of Education and Experience by Sex in Hong Kong, 1991-2011

	Education		*Experience*	
year	Male	Female	Male	Female
1991	9.003	9.336	22.092	18.101
1996	9.869	10.339	22.274	18.124
2001	10.514	10.813	22.766	19.181
2006	11.102	11.233	23.213	19.926
2011	11.617	11.692	24.340	21.220

Second, experience widened the group earnings differential. For instance, difference in experience between males and females accounted for nearly 18% of the overall earnings differential in 1991. According to Table 4.6, men on average were more experienced than women. Specifically, males in Hong Kong had acquired more than 3 years of work experience than females in every census year. Over time, however, the gap in experience between males and females shrank, although slightly. Thus, the contribution of experience to the gender earnings gap declined gradually from 1991 to 2011. In 2011, less than 10% of the gender earnings differential was due to experience.

Another finding from Table 4.5 is that an individual's occupation played a significant role in explaining the earnings gap. In each year, more than 50% of the explained gender earnings differential is due to the difference in occupation between males and females. Moreover, the contribution of occupation to the earnings gap grew steadily over time. In 1991, about 17% of the earnings gap was due to occupation differential. In 2011, difference in occupation accounted for more than 30% of the earnings differential in Hong Kong. Nevertheless, I have limited knowledge to determine where the difference in occupation comes from, i.e. from high-paid or low-paid occupations.

4.4 Recentered Influence Function Approach

The well-known Oaxaca-Blinder technique has a few limitations. First, it carries out the gender earnings difference only at the mean level. Nevertheless, it does not work for other percentiles of the distribution. In addition, it can neither address "glass ceiling" nor "sticky floor" problems when studying gender earnings gap. Therefore, researchers have developed other decomposition approaches to solve for these issues, such as a counterfactual analysis through a reweighting method proposed by DiNardo et al. (1996), conditional quantile regressions and sample bootstrapping proposed by Machado and Mata (2005), and Recentered Influence Function (RIF) by Firpo et al. (2009). In this study, I follow the RIF approach to examine the gender earnings gap in Hong Kong at different quantiles. In the RIF framework, the gender earnings gap at different quantiles is decomposed into components attributed to differences in individual characteristics and components due to differences in the returns to skills.

The Quantile Regression reports conditional estimates, while the RIF approach generates unconditional or marginal quantile estimates (Chi and Li 2008). By definition, the unconditional or marginal distribution function of Y can be illustrated as $F_Y(y) = \int F_{Y|X}(y|X = x) \cdot dF_X(x)$. Using the non-parametric kernel density estimates, q_τ, which is the τth quantile of the unconditional distribution of Y, and the corresponding density $f_Y(q_\tau)$ can be estimated. The influence function IF(Y; q_τ, F_Y), in general, measures the influence of a small change in the distribution of independent variable X to the unconditional distribution of Y at the τth quantile. In the case of quantiles, the influence function IF(Y; q_τ, F_Y) is equal to $(\tau - 1\{Y \leq q_\tau\})/f_Y(q_\tau)$. Note that $1\{Y \leq q_\tau\}$ is a dummy variable for whether the outcome variable Y is no greater than the quantile q_τ. The Recentered Influence Function (RIF) is simply the sum of the statistic q_τ and the influence function, i.e. RIF($Y; q_\tau, F_Y$) is equal to q_τ + IF($Y; q_\tau, F_Y$).

The RIF approach can be easily carried out as an ordinary least squares regression by replacing the dependent variable with the conditional expectation of the RIF($Y; v, F_Y$) (Fortin, Lemieux, and Firpo 2010). That is:

$$E[\mathrm{RIF}(Y;\ v, F_Y) \mid X] = X\beta + \varepsilon \tag{4.5}$$

where the parameters β can be estimated by OLS. To estimate the conditional expectation of RIF($Y; v, F_Y$), one can run either a probit or a logit model since it is a linear function of the probability whether the outcome variable Y is no greater than the quantile q_τ.

One of the advantages of the RIF method is that we can estimate the marginal effects of explanatory variables, such as education, experience, etc., on the targeted unconditional quantiles (Chi and Li 2008). The OLS estimates β does not estimate the marginal effect of X on Y; instead it reports the impact of X on the average Y in a given population. Firpo et al. (2009) claimed that the coefficient β_τ from a single conditional quantile regression cannot be used to estimate the impact of X on the corresponding unconditional quantile. The RIF approach is on the basis of influence function, thus it can be thought of as the contribution of an individual distribution to a given distributional statistic. Therefore, the marginal effect of an explanatory variable on the outcome variable at certain location could be estimated.

Before applying the RIF method to examine the contribution of each explanatory variable to the earnings differential, we need to estimate the earnings gap using the kernel density estimate method. By looking into the earnings distribution, I see that the female's earnings distribution is not perfectly smooth and it has a few spikes. Moreover, one of the spikes is far away from the center of the distribution especially for year 2011. Figure 4.3a, 4.3b, 4.3c plot the earnings distribution for females in 1991, 2001, and 2011 respectively. Taking 2011 as an example, the most significant spike is located at the 10^{th} percentile of the distribution with 7838 out of 7839 women engaging in elementary occupations. Similarly, the first significant spike of the female earnings distribution in 2001 is located at the 10^{th} percentile of the earnings distribution, with a vast majority of women engaging in elementary occupations.

When using the kernel density estimate, selection of bandwidth of the kernel might be problematic as given the distribution of sample data, a large bandwidth would oversmooth the density estimate while a smaller bandwidth would undersmooth the density estimate. Only the "optimal" bandwidth would result in a density estimate which is close to the true density. A convenient rule-of-thumb choice of bandwidth is $h^{*}=0.9AN^{-1/5}$, where A=min (σ, IQR/1.34), N is the sample observations, σ is the sample standard deviation and IQR is the interquartile range (Silverman 1986). As the female earnings distribution is not smooth, especially for year 2001 and 2011, I choose a smaller bandwidth than *h** for females to estimate the gender earnings gap [8].

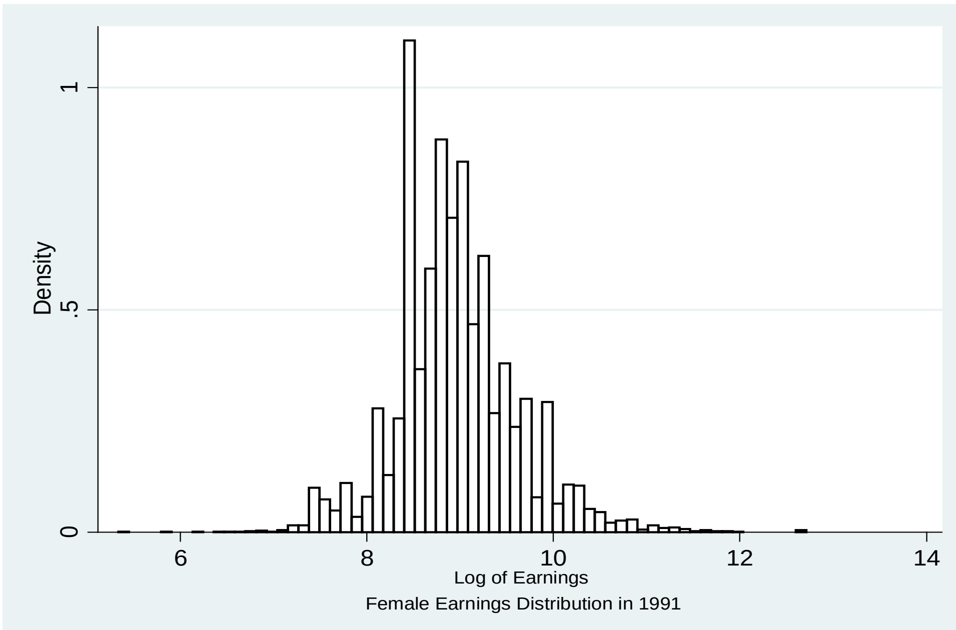

Figure 4.3a: Earnings distribution of Females in Hong Kong: 1991

[8] *h** is a good choice for males as the earnings distributions for males are relatively smooth. A smaller choice of bandwidth for females in a certain year yields a better estimate of the earnings gap between males and females. See Appendix Table B3 for more results.

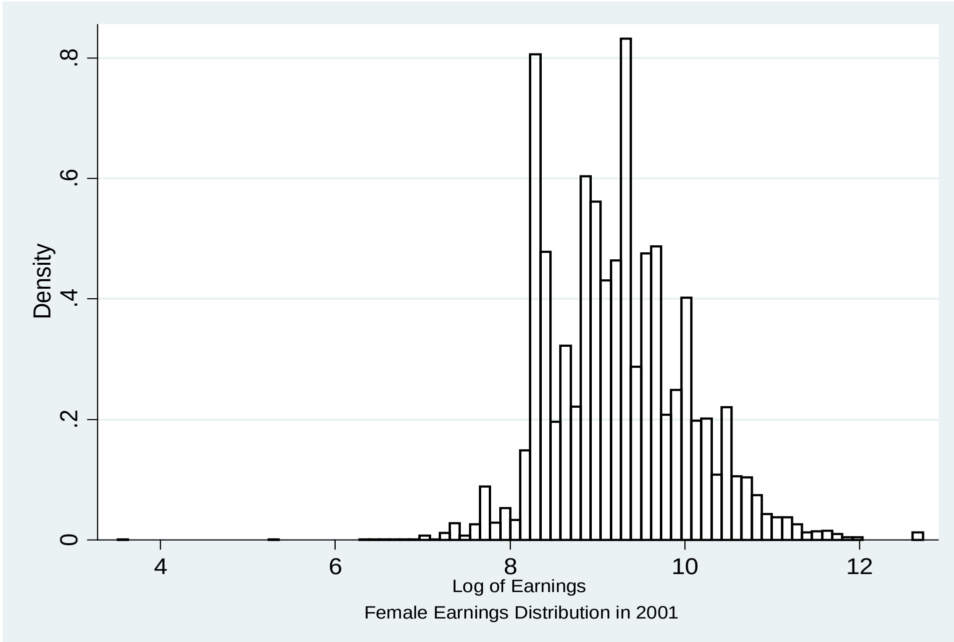

Figure 4.3b: Earnings distribution of Females in Hong Kong: 2001

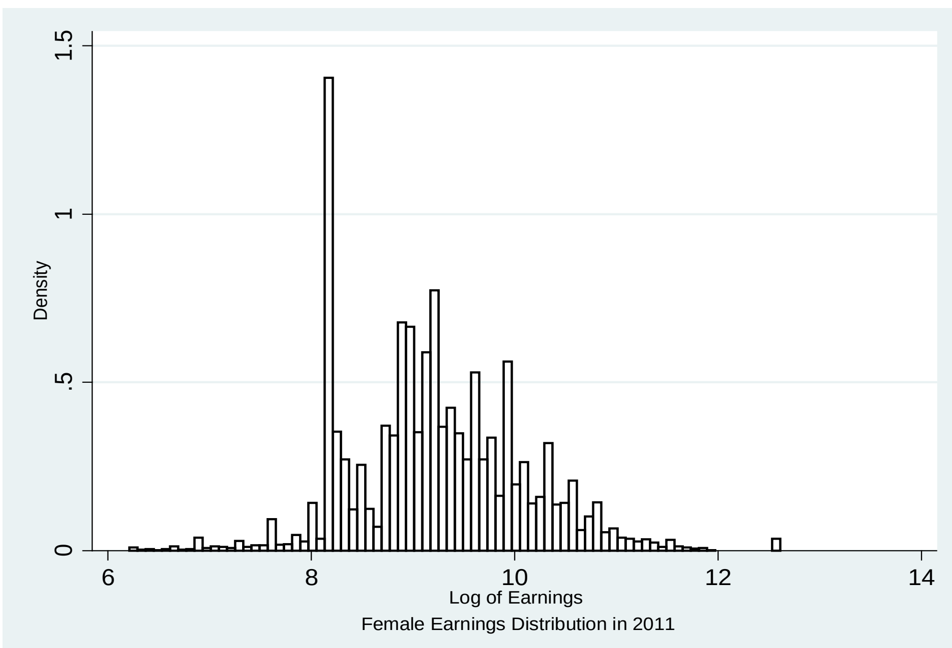

Figure 4.3c: Earnings distribution of Females in Hong Kong: 2011

After the kernel estimates, I apply the RIF method to examine the contribution of each explanatory variable to the gender earnings differential at selected quantiles. These estimates are documented in Table 4.7a, Table 4.7b, and Table 4.7c for 1991, 2001 and 2011, respectively. In general, some of the findings from these three tables are consistent with previous discussions. For instance, the lower tails of the earnings distribution have a relatively greater earnings gap in each year, but not the upper tails. In addition, differences in educational attainment between males and females reduce the gender earnings gap in each year, and at all percentiles, while experience has the opposite influence. Also, occupation is powerful at explaining the gap. These findings are consistent with the study of Ge et al. (2011) which concentrates on the year 2006 only.

Table 4.7a: Gender Earnings Gap in Hong Kong: Quantile Decomposition Results, 1991

	10th percentile	50th percentile	90th percentile
A. Raw Earnings gap:			
$Q_\tau(\ln(w_m)$-$Q_\tau(\ln(w_f))$	0.330	0.307	0.357
B. Mean RIF gap:			
$E[\mathrm{RIF}_\tau(\ln(w_m))]$-$E[\mathrm{RIF}_\tau(\ln(w_f))]$	0.341	0.355	0.326
	(0.023)	(0.014)	(0.023)
Explained Portion attributed to			
Education	-0.007	-0.009	-0.034
	(0.001)	(0.001)	(0.003)
Experience	0.032	0.044	0.116
	(0.002)	(0.001)	(0.005)
Duration in Hong Kong	0.014	0.009	-0.011
	(0.002)	(0.001)	(0.003)
Birth Place	0.025	-0.002	-0.003
	(0.006)	(0.002)	(0.008)
Occupation	-0.028	0.049	0.186
	(0.002)	(0.002)	(0.007)
Total explained by characteristics	0.037	0.092	0.255
	(0.007)	(0.004)	(0.013)

Table 4.7a continued.

Unexplained Portion attributed to			
Education	-0.116	-0.098	-0.057
	(0.045)	(0.016)	(0.134)
Experience	0.407	0.217	-0.003
	(0.021)	(0.017)	(0.103)
Duration in Hong Kong	0.118	0.004	-0.080
	(0.053)	(0.017)	(0.059)
Birth Place	-0.010	0.006	-0.075
	(0.060)	(0.019)	(0.070)
Occupation	-0.630	-0.194	0.065
	(0.266)	(0.043)	(0.128)
Constant	0.535	0.328	0.221
	(0.279)	(0.058)	(0.230)
Total unexplained portion	0.304	0.263	0.071
	(0.023)	(0.014)	(0.023)

Note: Bootstrapped standard errors are in parentheses.

Table 4.7b: Gender Earnings Gap in Hong Kong: Quantile Decomposition Results, 2001

	10th percentile	50th percentile	90th percentile
A. Raw Earnings gap:			
$Q_\tau(\ln(w_m)$-$Q_\tau(\ln(w_f))$	0.492	0.288	0.288
B. Mean RIF gap:			
$E[\mathrm{RIF}_\tau(\ln(w_m))]$-$E[\mathrm{RIF}_\tau(\ln(w_f))]$	0.492	0.383	0.283
	(0.004)	(0.005)	(0.017)
Explained Portion attributed to			
Education	-0.005	-0.012	-0.049
	(0.001)	(0.001)	(0.004)
Experience	0.018	0.046	0.128
	(0.002)	(0.001)	(0.006)
Duration in Hong Kong	0.044	0.020	-0.064
	(0.004)	(0.002)	(0.006)
Birth Place	0.058	0.021	0.083
	(0.008)	(0.004)	(0.009)
Occupation	0.043	0.112	0.222
	(0.004)	(0.003)	(0.009)
Total explained by characteristics	0.158	0.187	0.320
	(0.008)	(0.005)	(0.014)

Table 4.7b continued.

Unexplained Portion attributed to			
Education	0.137	-0.262	0.563
	(0.018)	(0.020)	(0.093)
Experience	0.443	0.182	0.301
	(0.015)	(0.013)	(0.056)
Duration at Hong Kong	0.173	-0.201	-0.242
	(0.024)	(0.019)	(0.041)
Birth Place	-0.322	-0.082	-0.243
	(0.025)	(0.022)	(0.057)
Occupation	0.430	0.116	-0.395
	(0.102)	(0.109)	(0.139)
Constant	-0.527	0.442	-0.020
	(0.106)	(0.115)	(0.180)
Total unexplained portion	0.334	0.196	-0.037
	(0.009)	(0.006)	(0.026)

Note: Bootstrapped standard errors are in parentheses.

Table 4.7c: Gender Earnings Gap in Hong Kong: Quantile Decomposition Results, 2011

	10th percentile	50th percentile	90th percentile
A. Raw Earnings gap:			
$Q_\tau(\ln(w_m)$-$Q_\tau(\ln(w_f))$	0.671	0.300	0.316
B. Mean RIF gap:			
$E[\text{RIF}_\tau(\ln(w_m))]$-$E[\text{RIF}_\tau(\ln(w_f))]$	0.676	0.305	0.319
	(0.004)	(0.014)	(0.017)
Explained Portion attributed to			
Education	-0.001	-0.003	-0.008
	(0.000)	(0.001)	(0.002)
Experience	0.006	0.033	0.072
	(0.001)	(0.002)	(0.003)
Duration in Hong Kong	0.032	0.017	-0.084
	(0.003)	(0.002)	(0.006)
Birth Place	0.033	0.008	0.020
	(0.006)	(0.002)	(0.007)
Occupation	0.082	0.133	0.156
	(0.003)	(0.004)	(0.006)
Total explained by characteristics	0.152	0.188	0.155
	(0.007)	(0.005)	(0.010)

Table 4.7c continued.

Unexplained Portion attributed to			
Education	0.184	0.494	-0.248
	(0.014)	(1.727)	(3.447)
Experience	0.399	0.518	-0.160
	(0.012)	(0.828)	(2.048)
Duration in Hong Kong	0.188	0.093	-0.348
	(0.016)	(0.755)	(0.348)
Birth Place	-0.090	-0.106	-0.371
	(0.018)	(0.242)	(0.178)
Occupation	0.505	0.260	0.101
	(0.144)	(0.368)	(0.144)
Constant	-0.661	-1.142	1.190
	(0.149)	(3.784)	(5.035)
Total unexplained portion	0.524	0.117	0.164
	(0.009)	(0.016)	(0.016)

Note: Bootstrapped standard errors are in parentheses.

Additional findings need to be noted. Firstly, a lot of the gender earnings differential at the 90^{th} percentile could be explained by the differences in individual characteristics, or the composition effect in each year. For instance, the composition effect accounts for 0.255 log points (78%) out of the 0.326 log points of the earnings gap at this location in 1991. In addition, occupational segregation makes the biggest contribution to the gender earnings gap at this percentile. Take the year 2011 as an example. Occupational segregation explains approximately 50% of the gender earnings gap at the 90^{th} percentile, while other factors such as experience only account for a rather small portion of the gap.

Secondly, covariates differences could only explain a small portion of the gender earnings gap at the 10^{th} percentile. In other words, a significant part of the differential at this percentile could not be explained by the difference in individual characteristics. For example, almost 90% of the earnings differential at the 10^{th} percentile cannot be explained by covariates differences in 1991. Two decades later, the composition effect can only explain a quarter of the gap, leaving three quarters of the gap unexplained by the composition effect, or three quarters of the gender earnings differential at the 10^{th} percentile is due to the difference in the returns to skills. To some extent, this implies that the gender earnings differential at lower percentiles is mainly due to the difference in the returns to skills.

Thirdly, over time the gender earnings gap converged slightly at the 90^{th} percentile, while it diverged significantly at the 10^{th} percentile. To understand such a big difference in the evolution of the gender earnings differential across percentiles, we might need to look at the distribution of employment by occupations for males and females in Hong Kong. Notice that the globalization and economic restructuring process in Hong Kong, especially the relocation of capital into Mainland China, has shifted the economy toward the service sector. In theory, the growth of the service sector leads to a rapid formation of a female labor force (Meyer 2003). We have observed in Hong Kong that female LFPR rose steadily from 1991 to 2011. However, the globalization process creates uneven impact among males and females. It results in the occupational polarization and deepening of gender inequality (Carr and Chen 2004). If occupational segregation is present, women tend to be over-represented in clerical, sales and service work, while men are predominant in production and managerial occupations (F. M. Cheung and Holroyd 2009) [9]. Certainly, occupational segregation will affect not only women's job opportunities but also their earnings, thus affect the gender earnings gap in Hong Kong.

Table 4.8 presents the trend of employment by occupation for males and females in Hong Kong from 1991 to 2011. The first two occupations in Table 8 are thought of as high-paid occupations [10]. On one hand, the number of women engaging in those occupations increased substantially from 3,619 in 1991 to 11,213 in 2011. Apparently, the number more than tripled. Alternatively, women made up about one quarter of those high-paid occupations in 1991, while approximately two-fifths of managers, administrators and professionals were females in 2011. On the other hand, only 7.73% of female labor force were doing managerial, administrative or

[9] Occupational segregation refers to the different distribution of men and women across different occupations.

[10] After estimating the mean earnings of each occupation, individuals in the first two occupations get paid significantly higher than individuals with other occupations, and individuals with elementary occupation earn the least.

professional jobs in 1991. In contrast, in 2011 about 13% of female labor force were engaged in those high-paid occupations. This makes a 67.7% increase in the percentage number of female labor force doing high-paid jobs over time. Clearly, more women had entered those prestigious jobs that used to be dominated by men. Such upgrade in female occupation certainly reduced the gender earnings gap at the upper percentiles.

Table 4.8: Employed Persons by Occupation Group and Sex in Hong Kong, 1991-2011

	1991		2001		2011	
	male	*female*	*male*	*female*	*male*	*female*
Managers and Administrators	9,017 [11.67]	2,131 [4.55]	12,144 [14.13]	4,502 [6.52]	11,522 [12.74]	6,301 [7.28]
Professionals	3,315 [4.29]	1,488 [3.18]	5,537 [6.44]	3,236 [4.68]	6,535 [7.23]	4,912 [5.68]
Associate Professionals	7748 [10.03]	5531 [11.80]	12892 [15.00]	11292 [16.34]	18130 [20.05]	16092 [18.60]
Craft and Related Workers	16,096 [20.83]	2,039 [4.35]	13,815 [16.07]	1,304 [1.89]	11,993 [13.26]	1,045 [1.21]
Plant and Machine Operators	10,976 [14.21]	6,046 [12.90]	9,823 [11.43]	1,534 [2.22]	9,092 [10.05]	682 [0.79]
Clerks	6,397 [8.28]	14,077 [30.04]	6,950 [8.08]	18,484 [26.75]	9,203 [10.18]	20,075 [23.21]
Service and Shop Sale Workers	10,636 [13.77]	5,738 [12.24]	12,465 [14.50]	10,693 [15.48]	13,291 [14.70]	14,360 [16.60]
Elementary Occupations	12,297 [15.92]	9,680 [20.65]	12,043 [14.01]	17,959 [25.99]	10,565 [11.68]	22,983 [26.57]

Note: numbers in brackets are percentages of respective labor force.

On the contrary, a lot of females entered the lowest-paid elementary occupations. In the meantime, male workers left and worked at a different occupation. In 1991, most of the workers employed in this occupation were men. However, women made up nearly 70% of this occupation in 2011. From the perspective of labor force participation, more than 25% of the female labor force were doing low-status and low-paid jobs compared to 11.68% of the male labor force in 2011. Obviously, the earnings difference between male and female workers at lower percentiles are significant. Moreover, it diverges over time. In addition, most of female labor force in this occupation were older and less-educated women, who had lost their jobs in the process of economic restructuring [11]. Those females with poor qualifications were not able to get better jobs. Individuals employed in this occupation tend to work as cleaners, domestic helpers and hand-packers, and their earnings tend to be low. Male workers doing the same type of jobs on average have more working experience. Thus, male workers tend to be paid a higher wage than female workers. Apparently, women at the bottom of the earnings distribution are disadvantaged in terms of earnings.

[11] In 2011, more than half of female labor force in this occupation were aged 40 and above. The average years of schooling of females was only 9 years.

Chapter 5

EARNINGS DIFFERENTIAL BETWEEN NATIVES AND CHINESE IMMIGRANTS IN HONG KONG: 1991-2011

5.1 Introduction

At present, Hong Kong is faced with some demographic challenges. On one hand, Hong Kong is one of the regions that have the low birth rates. In 2015, the crude birth rate in Hong Kong (8.2), which indicates the number of live births per 1,000 population, is way less than the worldwide average (19.081) (The World Bank 2017). On the other hand, Hong Kong has been experiencing an elderly problem for two reasons. First, the proportion of aged 65 or older continued increasing from 8.7% in 1991 to 13.3% in 2011, and second, the median age of the population had increased by 10 years from 1991 to 2011 (Census and Statistics Department of Hong Kong 2001; Census and Statistics Department of Hong Kong 2012a). Hong Kong might potentially have an aging population problem (Kao 2017).

A possible solution to those challenges for Hong Kong is to take more immigrants. On one hand, Hong Kong receives a maximum of 150 mainlanders daily under the One-Way Permits (OWPs) system. Apparently, the continued influx of Chinese immigrants supplements the labor force. On the other hand, Hong Kong has implemented several immigration policies to attract skilled talent and professionals who possess good educational qualifications or experience or skills from mainland China and foreign countries (GuideMeHongKong 2017). High-skilled immigrants contribute not only to the labor supply but also to innovation and technological change

(Anderson 2016). Certainly, Chinese immigrants will play a crucial role in shaping Hong Kong's present and future.

Studies on earnings differentials between natives and Chinese immigrants in Hong Kong are limited. Lam and Liu (2002) examined the earnings differential from 1981 to 1991, and found that earnings of Chinese male immigrants in Hong Kong diverged from those of the natives over time. By decomposing the earnings divergence using a two-equation model, they claimed that difference in returns to education is the main driver to the earnings divergence. Liu et al. (2004) studied the earnings differential between natives and immigrants through a decomposition method using the 1996 census data, and observed that immigrants had many barriers to occupational entry. In the meantime, they found that the differences in treatment within occupations contribute more to the earnings differential than unequal access to occupations. In short, immigrants in Hong Kong had a serious occupational segregation problem.

Because of the void in the literature, I have the unique opportunity to examine the trend in the earnings differential between natives and Chinese immigrants in Hong Kong and its underlying determinants over a 20-year period from 1991 to 2011. In this study, first I briefly discuss the history of Chinese immigrants in Hong Kong. Then I examine the trend in the earnings difference between natives and Chinese immigrants through several perspectives, including mean earnings differences, earnings gap by percentiles, and earnings gap by experience group. In the empirical analysis, I apply the Oaxaca-Blinder decomposition method to investigate the determinants of the earnings differential at the mean level. In addition, I apply the Recentered Influence Function method to the earnings gap at different quantiles and their corresponding determinants.

This study makes two important contributions. First, the studies on earnings differential between natives and Chinese immigrants in Hong Kong are limited and the most recent trend in the earnings differential is unknown. Thus, my study will certainly fill in the literature gap in Hong Kong by using census/by-census datasets from 1991 to 2011. This study will not only examine how earnings inequality between natives and Chinese immigrants evolves over a 20-year period, but also investigate its underlying determinants. Second, more than solely concentrating on the mean level of earning by using the widely-used Oaxaca-Blinder decomposition method, this study also investigates the earnings gap at different earnings percentiles by using the Recentered Influence Function method, which allows me to address potential “sticky floor” and “glass ceiling” problems in Hong Kong.

The remaining sections of the paper are organized as follows: Section 2 discusses the history of Chinese immigrants in Hong Kong. Section 3 outlines earnings for natives and Chinese immigrants. Section 4 discusses the Oaxaca-Blinder technique. Section 4 presents the Recentered Influence Function (RIF) method with unconditional quantile and decomposition technique.

5.2 A Brief History of Hong Kong Immigration

Hong Kong had been colonized by the United Kingdom since the First Opium War of 1839-1842 between the United Kingdom and the Qing Dynasty of China till July 1997. After the British established Hong Kong as a free port, the population in Hong Kong expanded significantly during the 1840s through the 1860s as mainland Chinese began migrating to Hong Kong (GuideMeHongKong 2017). Before 1949, mainland Chinese could freely move in and out of Hong Kong under the Peking Treaty Signed by the Qing Dynasty and Great Britain in 1898 (Liu et al. 2004). After

World War II, large numbers of Chinese immigrants migrated into Hong Kong for political or economic reasons (Lam and Liu 2002). Specifically, mainland Chinese came to Hong Kong mostly for reuniting with families or escaping communism in the 1950s. In addition, the collapse of agricultural production following collectivization and the Great Leap Forward movement in China resulted in a large flow of mainland Chinese without entry visas or permits to Hong Kong (Lam and Liu 2002; Liu et al. 2004). Fortunately, Hong Kong admitted all entrants and allowed them to stay till 1974.

In 1974, Hong Kong's immigration policy was changed to a "touch-base" policy. Illegal immigrants were repatriated to mainland China once they were caught at the border of Hong Kong, while those were given permission to stay and work in Hong Kong if they evaded capture and found a place of accommodation or established a home with relatives. After 7 years of residence, they would become permanent residents. A massive wave of illegal immigrants took advantage of the weakened control and crossed the border since the open-door economic reform was implemented in mainland China in 1979. The population of Hong Kong increased rapidly in 1979-1980 and the massive inflow of illegal immigrants caused such disruption that the "touch-base" policy became unsustainable. Thus, this policy was terminated in October 1980 with the cooperation of mainland China. Since then, immigrants from mainland China have been legal with an exit permit issued by the Chinses authorities. Illegal immigrants would be repatriated immediately once identified and captured.

At present, Hong Kong has been fully implementing the one-way permit quota system under which a maximum of 150 legal immigrants from mainland China a day are allowed to come to settle in Hong Kong permanently. The permit is specifically for the purpose of family reunification [12]. Since the handover from Great Britain to China in 1997, 830,000 mainland Chinese have come to settle in Hong Kong on one-way permits and it is projected that 1.93 million new immigrants will settle in Hong Kong in the next five decades, with most of them coming from mainland China. (GovHK 2016). Apparently, immigrants from mainland China will drive the population growth in Hong Kong in the future. In the meantime, Hong Kong has introduced several immigration polies to attract skilled talent and professionals from mainland China and foreign countries as well (GuideMeHongKong 2017).

5.3 Descriptive Statistics

From 1991 to 2011, the immigrant workforce (including Chinese and non-Chinese immigrants) had increased steadily in Hong Kong. However, the number of Chinese immigrants did not change much over the whole period. Instead, the number of non-Chinese immigrants had increased rapidly. This could be seen from Table 5.1. In 1991, a majority of immigrants were made up of Chinese. By 2011, only 70% of immigrants were Chinese immigrants, and the rest were non-Chinese immigrants. Over time, the percentage number of Chinese immigrants out of the total population had decreased by 10.5 percentage points from 35.6% in 1991 to 25.1% in 2011.

[12] Cross-border marriages have become increasingly common with a spouse from mainland China. According to the Annual Digest of Statistics, more than 60% of the new arrivals from mainland China holding one-way permit are females and a majority of them are aged between 25 and 44.

Table 5.1: Demographic Statistics of Natives and Immigrants in Hong Kong: 1991-2011

	1991	1996	2001	2006	2011
Natives	72,553	88,966	97,481	107,276	114,313
All Immigrants	52,250	57,905	58,347	56,683	64,101
Chinese Immigrants	44,431	45,511	43,737	42,190	44,819
non-Chinese Immigrants	7,819	12,394	14,610	14,493	19,282

Table 5.2 summarizes the overall trends in earnings and earnings difference between natives and Chinese Immigrants from 1991 to 2011. From Panel A we can see that over time, mean earnings had increased for both natives and Chinese immigrants, and the rise in earnings was much higher for natives (40.5%) than for Chinese immigrants (22.8%). As a result, the mean earnings difference between natives and Chinese immigrants had increased substantially from 0.214 log points in 1991 to 0.349 log points. Put in another way, the mean earnings gap between natives and Chinese immigrants had widened by more than 60% from 1991 to 2011. Panels B and C display statistics for males and females respectively. Apparently, the mean earnings difference between natives and Chinese immigrants is substantially higher for females than for males in each year. Thus, most of the overall earnings difference between natives and Chinese immigrants comes from females. In the meantime, the earnings gap had widened for both males and females, which diverges the overall earnings difference between natives and Chinese immigrants. After taking all other non-Chinese immigrants into consideration, over time the overall earnings gap between natives and all immigrants has diverged even more, and females have significant influence on the overall earnings differential. The results are presented in Appendix Table C1. The earnings gap for males is relatively small and it remains stable over time. This indicates that the male non-Chinese immigrants on average earn

more income than male Chinese immigrants. On the contrary, female non-Chinese immigrants on average earn less than female Chinese immigrants.

Table 5.2: Overall Earnings Trends for Natives and Chinese Immigrants in Hong Kong: 1991-2011

	1991		1996		2001		2006		2011	
	Natives	Chinese	Natives	Chinese	Natives	Chinese	Natives	Chinese	Natives	Chinese
Panle A. Overall										
Mean Earnings	9.245	9.031	9.435	9.171	9.596	9.292	9.555	9.247	9.585	9.236
Std. Dev	0.660	0.658	0.695	0.688	0.744	0.709	0.784	0.729	0.807	0.751
N	72,553	44,431	88,966	45,511	97,481	43,737	107,276	42,190	114,313	44,819
Mean Difference	0.214		0.263		0.304		0.308		0.349	
Panel B. Male										
Mean Earnings	9.352	9.161	9.509	9.275	9.681	9.437	9.620	9.399	9.643	9.398
Std. Dev	0.667	0.626	0.708	0.674	0.746	0.684	0.789	0.707	0.800	0.726
N	42,996	31,219	52,893	30,872	55,552	27,086	60,390	23,869	63,761	23,507
Mean Difference	0.190		0.235		0.244		0.220		0.245	
Panel C. Female										
Mean Earnings	9.089	8.723	9.326	8.954	9.482	9.055	9.471	9.048	9.512	9.058
Std. Dev	0.619	0.628	0.660	0.668	0.726	0.685	0.769	0.709	0.811	0.738
N	29,557	13,212	36,073	14,639	41,929	16,651	46,886	18,321	50,552	21,312
Mean Difference	0.366		0.372		0.427		0.423		0.455	

Source: Census and By-census datasets, compiled

More than concentrating solely on the mean level of earnings, I examine the trend in earnings differential by deciles over time. Table 5.3 illustrates the overall earnings gap between natives and Chinese immigrants by each decile of their respective earnings distribution for each year. In most years, the earnings gap was found to be bigger at higher deciles than other deciles in general. For instance, the earnings differential in 2011 for the 80^{th} percentile (0.511) and 90^{th} percentile (0.470) individuals was substantially bigger than other percentiles. In addition, the bottom decile has a relatively bigger earnings gap than other lower deciles in most years. The earnings gap for the 10^{th} percentile declined moderately from 1996 to 2011. In contrast, the gap rose steadily for the median and increased substantially for the 90^{th} percentile over the whole period.

Table 5.3: The Earnings Differential between Natives and Chinese Immigrants in Hong Kong by Distribution Percentiles: 1991-2011

	Percentile								
	10th	*20th*	*30th*	*40th*	*50th*	*60th*	*70th*	*80th*	*90th*
1991	0.182	0.288	0.169	0.163	0.182	0.185	0.208	0.261	0.319
1996	0.318	0.260	0.208	0.182	0.186	0.274	0.310	0.325	0.318
2001	0.288	0.223	0.251	0.223	0.234	0.395	0.365	0.374	0.405
2006	0.262	0.241	0.284	0.288	0.302	0.336	0.348	0.348	0.409
2011	0.262	0.208	0.288	0.302	0.357	0.440	0.431	0.511	0.470

Note: The earnings gap is the earnings of natives at a certain decile minus the earnings of Chinese immigrants at the same decile.

By looking at all the immigrants including non-Chinese, I see a very different story. The results are presented in Appendix Table C2. In each year, the earnings gap between natives and all immigrants was found to be larger at lower deciles than other deciles. In addition, the earnings differential at the 90th percentile tends to be very small within each year. This suggests that some of the non-Chinese immigrants are at the very top of the earnings distribution, and most of them are males according to Appendix Table C1. Meanwhile, this also implies that Chinese immigrants might experience a "glass ceiling" problem in Hong Kong.

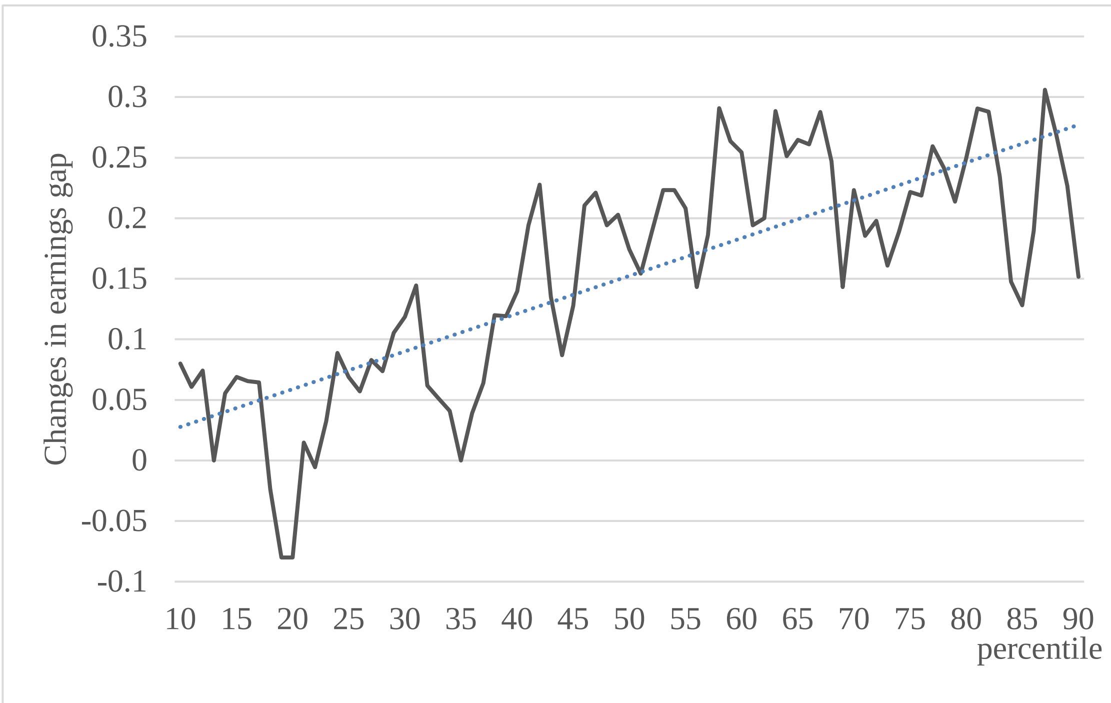

Figure 5.1: Changes in the Earnings Gap between Natives and Chinese Immigrants by Percentile in Hong Kong: 1991-2011

Figure 5.1 plots the changes in the earnings gap between natives and Chinese immigrants from 1991 to 2011 by selected percentiles. Clearly, I see an upward trend in the changes in the earnings gap from 1991 to 2011. That is to say, the earning gap widens towards the upper percentiles. Thus, the earnings divergence at the upper segments contributed a lot to the widening of the overall earnings gap between natives and Chinese immigrants from 1991 to 2011.

Table 5.4: Natives-Chinese Immigrants Earnings Differentials in Hong Kong by Potential Experience Level: 1991-2011

	1991	1996	2001	2006	2011
All Experience Levels	0.214	0.263	0.304	0.308	0.349
0-5	0.154	0.032	0.030	0.167	0.180
6-10	0.232	0.168	0.147	0.113	0.216
11-15	0.238	0.256	0.324	0.196	0.171
16-20	0.188	0.281	0.417	0.436	0.309
21-25	0.118	0.243	0.379	0.478	0.575
26-30	0.084	0.173	0.256	0.415	0.550
31-35	0.128	0.134	0.136	0.272	0.441

Note: Standard errors for "all experience levels" estimates are approximately 0.004 in each year. Standard errors for individual-experience level estimates range from 0.008 to 0.016.

Table 5.4 presents the earnings differential between natives and Chinese immigrants by potential experience level from 1991 to 2011. Following cohorts down the diagonal, I see that the earnings differential diverged for almost all groups over time. In other words, as the cohort has acquired more experience, earnings inequality has grown for the same cohort. As a result, most of the earnings differential between natives and Chinese immigrants had been concentrated on the more experienced groups in 2011. Over the whole period (comparison of the first and last column), the earnings gap diverged at upper levels of potential experience, while it converged at lower levels of experience. Put in another way, the earnings gap widened between more experienced natives and Chinese immigrants. Notice that more experienced individuals tend to be located at the upper percentiles of the earnings distribution, thus the findings from this table are consistent with previous tables.

5.4 Oaxaca-Blinder Decomposition Approach

The Oaxaca-Blinder decomposition method is one of the most popular approaches to study gender earnings disparity. In the meantime, it has been widely applied to the study of the earnings disparity between natives and immigrants (Borjas 1985; Gabriel and Schmitz 1987; George and Kuhn 1994). This approach decomposes mean differences in log earnings in linear regression models in a counterfactual manner. Thus, native-immigrant earnings differentials are divided into a part that is "explained" by group differences in individual characteristics such as education and experience, and a part that is "unexplained" (Oaxaca 1973; Blinder 1973). Specifically, following a typical Mincer-type wage equation, the earnings variable is regressed on a set of explanatory factors for natives and immigrants separately. That is,

$$Y_i = X_i\beta + \varepsilon_i \tag{5.1}$$

where Y_i is the log earnings of individual i, and X_i is a set of individual characteristics, β is a vector of coefficients, and ε_i is a residual term assumed to be normally distributed with mean zero and constant variance. Thus, the difference between the two groups' means can be expressed as

$$\bar{Y}_n - \bar{Y}_i = \bar{X}_n\hat{\beta}_n - \bar{X}_i\hat{\beta}_i \tag{5.2}$$

where n = natives and i = immigrants. The next step is to add and subtract the term $\bar{X}_n\hat{\beta}_i$ ($\bar{X}_i\hat{\beta}_n, alternatively$) to the right side of the equation as follows:

$$\bar{Y}_n - \bar{Y}_i = (\bar{X}_n\hat{\beta}_n - \bar{X}_n\hat{\beta}_i) + (\bar{X}_n\hat{\beta}_i - \bar{X}_i\hat{\beta}_i) \tag{5.3}$$

The term $\bar{X}_n\hat{\beta}_i$ is treated as a counterfactual, representing the wage immigrants would have earned under the natives' wage structure. By rearranging terms in Equation 5.3, I obtain the following expression:

$$\bar{Y}_n - \bar{Y}_i = (\bar{X}_n - \bar{X}_i)\hat{\beta}_i + \bar{X}_n(\hat{\beta}_n - \hat{\beta}_i) \tag{5.4}$$

The first term on the right side of Equation 5.4 represents the "explained" portion of earnings difference or the composition effect. It measures the group wage difference due to covariate differences. The second term represents the "unexplained" portion of earnings differences. The coefficient estimates are presented in Appendix Table C3.

Table 5.5 presents a summary of the Oaxaca-Blinder decomposition method estimates for Hong Kong since 1991. Panel A shows the trend in earnings gap between natives and Chinese immigrants and the portion of earnings differential being explained by differences in personal characteristics. As shown in Panel A, the earnings gap in Hong Kong widened moderately from 1991 to 2011. The portion of earnings differential explained by covariates difference grew steadily from 1991 to 2011. Note that less than half of earnings differentials is due to the difference in individual characteristics in 1991. In contrast, covariates differences account for more than three quarters of the earnings gap in 2011. Certainly, the Oaxaca-Blinder approach has significant explanatory power in explaining the earnings difference between natives and Chinese immigrants. This approach yields a similar result when applying to the earnings difference between natives and all immigrants. The results are presented in Appendix Table C4.

Table 5.5: Summary of Oaxaca-Blinder Decomposition Method Estimates of Earnings Differential between Natives and Chinese Immigrants in Hong Kong, 1991-2011

	1991	1996	2001	2006	2011
Panel A. Earnings Differential					
Overall Gap	0.214	0.263	0.304	0.308	0.349
% Explained	43.23	50.54	60.21	65.47	77.39
Panel B. Contribution of Covariates Differences to Earnings Differential					
Education	0.193	0.157	0.157	0.157	0.163
	[90.44]	[59.60]	[51.65]	[50.96]	[46.87]
Experience	-0.174	-0.111	-0.111	-0.114	-0.068
	[-81.68]	[-42.20]	[-36.57]	[-36.95]	[-19.55]
Gender	-0.024	-0.013	-0.013	0.000	0.004
	[-11.26]	[-4.88]	[-4.23]	[-0.10]	[1.01]
Occupation	0.098	0.100	0.122	0.159	0.171
	[45.74]	[38.02]	[40.10]	[51.56]	[49.07]

Note: Each main entry of this table represents the contribution of each characteristic to the overall gap. Its percentage is in brackets.

Panel B of Table 5.5 illustrates the contribution of each individual characteristic to the overall earnings gap in each year. Several findings need to be noted. First, experience reduced the earnings gap between natives and Chinese immigrants. However, its influence on the earnings gap decreased over time. Chinese immigrants tend to have more experience than natives. As shown in Table 5.6, the difference in the potential work experience between Chinese immigrants and natives is very large although it has decreased over time.

Table 5.6: Descriptive Statistics of Education and Experience in Hong Kong:1991-2011

year	*Education*		*Experience*	
	Natives	Chinese Immigrants	Natives	Chinese Immigrants
1991	10.006	7.381	15.100	29.409
1996	10.625	8.533	17.037	27.919
2001	11.268	8.942	18.251	28.370
2006	11.771	9.618	19.561	27.614
2011	12.318	10.054	21.290	27.646

Second, education diverged the group earnings differential. Despite the fact that the contribution of education to the overall earnings gap declined all the time, the difference in years of schooling between natives and Chinese immigrants could still account for almost half of the earnings gap in 2011. More details could be seen from Table 5.6. In each year, natives have at least two more years of schooling than Chinese immigrants. In addition, Chinese immigrants on average barely went to high school from 1991 to 2001, and obtained about one year of training in high school. Moreover, the training received by Chinese immigrants in school before migrating to Hong Kong in general has a lower quality than the one provided in Hong Kong.

An additional finding from Table 5 is that occupation difference between natives and Chinese immigrants played an important role in explaining the earnings difference. Specifically, the contribution of individual's occupation to the overall earnings gap remained steady over time. In each year around 40% or more of the earnings gap could be accounted for by occupation difference. Nevertheless, I have limited knowledge to determine where the difference in occupation comes from, i.e. from high-paid or low-paid occupations.

5.5 Recentered Influence Function Approach

The well-known Oaxaca-Blinder technique has a few limitations. First, when applied to earnings difference between natives and Chinese immigrants, it can only carry out the earnings difference at the mean level. Nevertheless, it does not work for other percentiles. In addition, it can neither address “glass ceiling” nor “sticky floor” problems when studying native-immigrant earnings gap. Therefore, researchers have developed other decomposition approaches to solve for these issues, such as a counterfactual analysis through a reweighting method proposed by DiNardo et al. (1996), conditional quantile regressions and sample bootstrapping proposed by Machado and Mata (2005), and Recentered Influence Function (RIF) by Firpo et al. (2009). In this study, I follow the RIF approach to examine the earnings gap between natives and Chinese immigrants in Hong Kong at different quantiles. In the RIF framework, the earnings gap at different quantiles is decomposed into components attributed to differences in individual characteristics and components due to differences in the returns to skills.

The Quantile Regression reports conditional estimates, while the RIF approach generates unconditional or marginal quantile estimates (Chi and Li 2008). By definition, the unconditional or marginal distribution function of Y can be illustrated as $F_Y(y) = \int F_{Y|X}(y|X = x) \cdot dF_X(x)$. Using the non-parametric kernel density estimates, q_τ, which is the τth quantile of the unconditional distribution of Y, and the corresponding density $f_Y(q_\tau)$ can be estimated. The influence function IF(Y; q_τ, F_Y), in general, measures the influence of a small change in the distribution of independent variable X to the unconditional distribution of Y at the τth quantile. In the case of quantiles, the influence function IF(Y; q_τ, F_Y) is equal to $(\tau - 1\{Y \leq q_\tau\})/f_Y(q_\tau)$. Note that $1\{Y \leq q_\tau\}$ is a dummy variable for whether the outcome variable Y is no greater than the quantile q_τ. The Recentered Influence Function (RIF) is simply the sum of the statistic q_τ and the influence function, i.e. RIF($Y; q_\tau, F_Y$) is equal to q_τ + IF($Y; q_\tau, F_Y$).

The RIF approach can be easily carried out as an ordinary least squares regression by replacing the dependent variable with the conditional expectation of the RIF($Y; v, F_Y$) (Fortin, Lemieux, and Firpo 2010). That is:

$$E[\mathrm{RIF}(Y;\ v, F_Y) \mid X] = X\beta + \varepsilon \tag{5.5}$$

where the parameters β can be estimated by OLS. To estimate the conditional expectation of RIF($Y; v, F_Y$), one can run either a probit or a logit model since it is a linear function of the probability whether the outcome variable Y is no greater than the quantile q_τ.

One of the advantages of the RIF method is that we can estimate the marginal effects of explanatory variables, such as education, experience, etc., on the targeted unconditional quantiles (Chi and Li 2008). The OLS estimate β does not estimate the marginal effect of X on Y; instead it measures the impact of X on the average Y in a given population. Firpo et al. (2009) claimed that the coefficient β_τ from a single conditional quantile regression cannot be used to estimate the impact of X on the corresponding unconditional quantile. The RIF approach is on the basis of influence function, thus it can be thought of as the contribution of an individual distribution to a given distributional statistic. Therefore, the marginal effect of an explanatory variable on the outcome variable at certain location could be estimated.

The first step of the RIF method is to estimate the earnings gap using the kernel density estimate method. By looking into the earnings distribution for natives and Chinese immigrants respectively, I find that some of the earnings distributions are not perfectly smooth. For instance, the earnings distribution for Chinese immigrants in 1991 is not smooth and has more than one spike. Similarly, natives have an earnings distribution with at least three spikes in 2001. This could be seen in Figure 5.2a, 5.2b and 5.2c. When using the kernel density estimate, selection of bandwidth of the kernel might be problematic given the distribution of the sample data, a large bandwidth would oversmooth the density estimate while a smaller bandwidth would undersmooth the density estimate. Only the "optimal" bandwidth would result in a density estimate which is close to the true density. A convenient rule-of-thumb choice of bandwidth is $h^{*}=0.9AN^{-1/5}$, where A=min (σ, IQR/1.34), N is the sample observations, σ is the sample standard deviation and IQR is the interquartile range (Silverman 1986). Thus, I follow the rule-of-thumb way to choose the bandwidth h^{*} for smoothed earnings distributions, and tend to choose a smaller bandwidth for those unsmoothed earnings distributions. Comparisons of bandwidth selections are presented in Appendix Table C5.

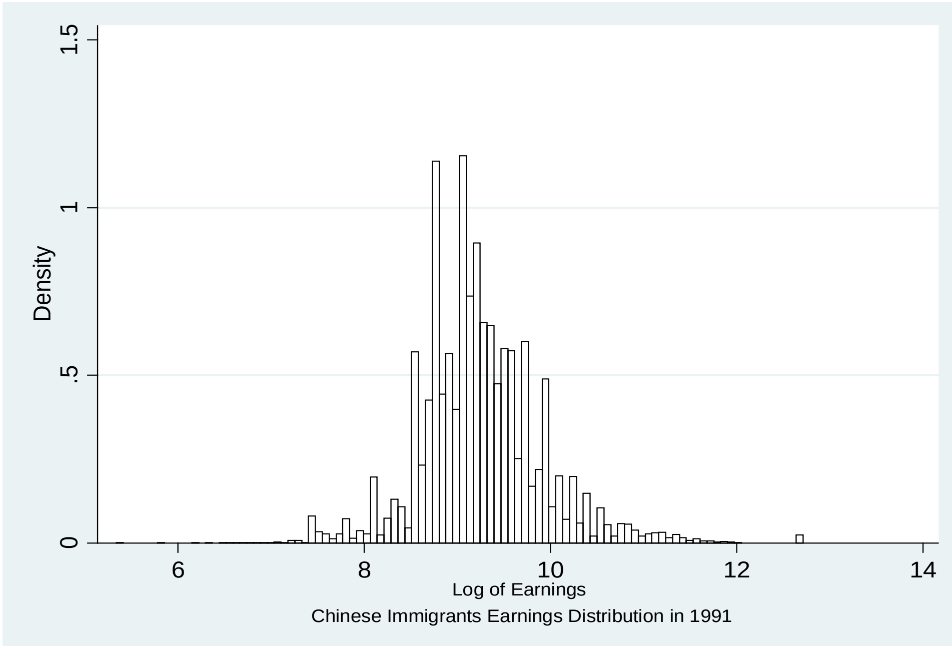

Figure 5.2a: Earnings Distribution of Chinese Immigrants in Hong Kong: 1991

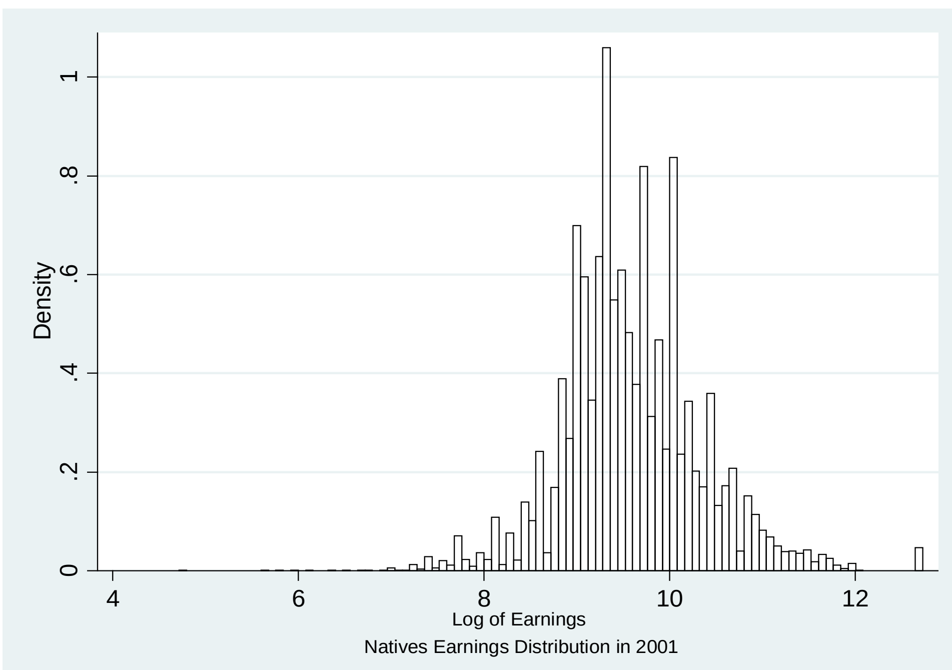

Figure 5.2b: Earnings Distribution of Natives in Hong Kong: 2001

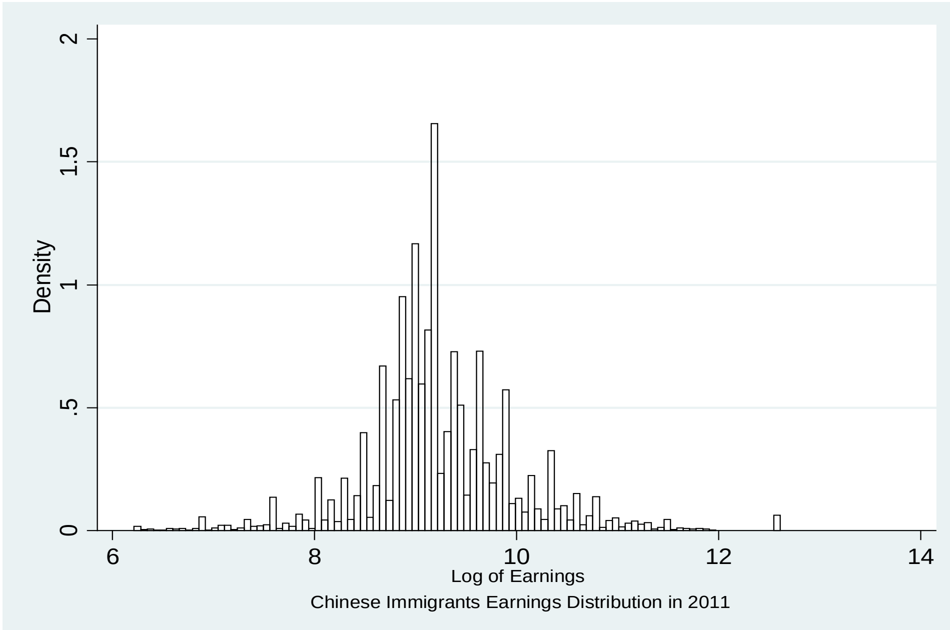

Figure 5.2c: Earnings Distribution of Chinese Immigrants in Hong Kong: 2011

After the kernel estimates, I apply the RIF method to examine the contribution of each explanatory variable to the earnings differential between natives and Chinese immigrants at selected quantiles. These estimates are documented in Table 5.7a, Table 5.7b, and Table 5.7c for 1991, 2001 and 2011, respectively. Some of the findings from these three tables are consistent with previous results. For instance, the earnings gap grows towards the upper percentiles. In addition, females' earnings differential tends to be larger than males'. In general, potential working experience contributes to the narrowing of the earnings gap while years of schooling widens the gap. Moreover, occupation is powerful at explaining the earnings gap between natives and Chinese immigrants.

Table 5.7a: Earnings Differential between Natives and Chinese Immigrants in Hong Kong: Quantile Decomposition Results, 1991

	10^{th} percentile	50^{th} percentile	90^{th} percentile
Raw Earnings Gap: $Q_\tau(\ln(w_n))$-$Q_\tau(\ln(w_c))$	0.182	0.182	0.318
Mean RIF Gap: $E[RIF_\tau(\ln(w_n))]$- $E[RIF_\tau(\ln(w_c))]$	0.183	0.188	0.319
	(0.009)	(0.002)	(0.026)
Explained Portion attributed to			
Male	-0.033	-0.025	-0.011
	(0.001)	(0.001)	(0.002)
Education	0.100	0.167	0.357
	(0.005)	(0.004)	(0.070)
Experience	0.003	-0.155	-0.422
	(0.007)	(0.005)	(0.082)
Occupation	0.121	0.090	0.076
	(0.003)	(0.002)	(0.015)
Total explained by characteristics	0.192	0.077	-0.000
	(0.007)	(0.004)	(0.008)
Unexplained Portion attributed to			
Male	0.074	0.099	0.060
	(1.381)	(0.003)	(0.175)
Education	0.238	0.452	0.957
	(0.473)	(0.009)	(0.903)
Experience	0.246	0.617	1.144
	(0.498)	(0.011)	(1.401)
Occupation	0.146	-0.104	-0.164
	(3.048)	(0.035)	(0.732)
Constant	-0.713	-0.952	-1.677
	(5.400)	(0.041)	(3.166)
Total unexplained portion	-0.009	0.111	0.320
	(0.011)	(0.005)	(0.025)

Note: Bootstrapped standard errors in parentheses

Table 5.7b: Earnings Differential between Natives and Chinese Immigrants in Hong Kong: Quantile Decomposition Results, 2001

	10^{th} percentile	50^{th} percentile	90^{th} percentile
Raw Earnings Gap: $Q_\tau(\ln(w_n))$-$Q_\tau(\ln(w_c))$	0.288	0.234	0.405
Mean RIF Gap: $E[RIF_\tau(\ln(w_n))]$- $E[RIF_\tau(\ln(w_c))]$	0.230	0.261	0.415
	(0.005)	(0.003)	(0.018)
Explained Portion attributed to			
Male	-0.007	-0.004	-0.006
	(0.000)	(0.000)	(0.001)
Education	0.053	0.113	0.546
	(0.002)	(0.003)	(0.023)
Experience	0.002	-0.076	-0.412
	(0.003)	(0.003)	(0.018)
Occupation	0.078	0.095	0.107
	(0.002)	(0.002)	(0.007)
Total explained by characteristics	0.126	0.127	0.235
	(0.004)	(0.003)	(0.014)
Unexplained Portion attributed to			
Male	-0.194	-0.126	0.036
	(0.009)	(0.005)	(0.013)
Education	0.035	0.338	1.649
	(0.019)	(0.014)	(0.105)
Experience	0.062	0.279	1.134
	(0.019)	(0.014)	(0.102)
Occupation	-0.471	-0.172	-0.333
	(0.164)	(0.061)	(0.173)
Constant	0.672	-0.185	-2.305
	(0.168)	(0.063)	(0.255)
Total unexplained portion	0.103	0.134	0.180
	(0.006)	(0.004)	(0.022)

Note: Bootstrapped standard errors in parentheses

Table 5.7c: Earnings Differential between Natives and Chinese Immigrants in Hong Kong: Quantile Decomposition Results, 2011

	10^{th} percentile	50^{th} percentile	90^{th} percentile
Raw Earnings Gap: $Q_\tau(\ln(w_n))$-$Q_\tau(\ln(w_c))$	0.262	0.357	0.470
Mean RIF Gap: $E[RIF_\tau(\ln(w_n))]$- $E[RIF_\tau(\ln(w_c))]$	0.262	0.338	0.400
	(0.005)	(0.013)	(0.009)
Explained Portion attributed to			
Male	0.007	0.002	0.003
	(0.001)	(0.000)	(0.000)
Education	0.054	0.160	0.260
	(0.003)	(0.003)	(0.006)
Experience	0.026	-0.074	-0.131
	(0.003)	(0.002)	(0.003)
Occupation	0.163	0.181	0.129
	(0.004)	(0.003)	(0.004)
Total explained by characteristics	0.248	0.268	0.260
	(0.005)	(0.005)	(0.006)
Unexplained Portion attributed to			
Male	0.053	-0.082	0.002
	(0.005)	(0.130)	(0.026)
Education	0.180	0.543	0.718
	(0.017)	(0.196)	(0.385)
Experience	0.322	0.445	0.471
	(0.017)	(0.265)	(0.294)
Occupation	0.764	-0.215	-0.407
	(0.228)	(0.252)	(0.210)
Constant	-1.305	-0.621	-0.645
	(0.225)	(0.814)	(0.902)
Total unexplained portion	0.014	0.069	0.140
	(0.007)	(0.012)	(0.009)

Note: Bootstrapped standard errors in parentheses

Additional findings need to be noted. First, covariates difference can account for a significant portion of earnings difference between natives and Chinese immigrants at the 10th percentile. For instance, more than 90% of the earnings gap at this location in 1991 and 2011 is due to the difference in personal characteristics, such as schooling, work experience, and occupation. Generally, potential working experience helps reduce the earnings gap, but not at the 10th percentile. In 2011, difference in work experience accounts for 10% of the earnings gap at the bottom. In addition, more than 50% of the explained earnings gap is due to the difference in occupations between natives and Chinese immigrants. Apparently, occupational segregation plays an important role in explaining the earnings differential at the 10th percentile.

Second, a different pattern presents at the 90th percentile. In 1991, covariates difference can barely explain any of the earnings difference between natives and Chinese immigrants at the 90th percentile. In other words, the earnings gap at the 90th percentile in 1991 is totally due to the difference in returns to skills and other unknown factors. In 2001 and 2011, differences in personal characteristics account for more than 50% of the earnings gap at the 90th percentile. For example, the composition effect accounts for 0.260 log points (55%) out of the 0.415 log points of earnings gap at this location in 2001. In addition, occupational segregation explains approximately 50% of the earnings gap at the 90th percentile in 2001 and 2011.

Third, in general the earnings difference between natives and Chinese immigrants diverged at both the bottom and the top percentiles over time. From the discussion above, we understand that occupational segregation accounts for a big portion of the earnings gaps for both the 10th and 90th percentiles. Thus, it would be necessary to examine the distribution of employment by occupations for natives and Chinese immigrants in Hong Kong. The results are presented in Table 5.8. Note that the first two occupations in the table are treated as high-paid occupations and elementary occupation is the lowest-paid one [13].

Table 5.8: Employed Persons by Occupation Group and Immigration Status in Hong Kong, 1991-2011

	1991		2001		2011	
	Natives	Chinese	Natives	Chinese	Natives	Chinese
Managers and Administrators	5,936	4,233	10,718	4,387	13,037	3,095
	(8.18)	(9.53)	(10.99)	(10.03)	(11.40)	(6.91)
Professionals	3,477	714	6,929	1,142	9,199	1,446
	(4.79)	(1.61)	(7.11)	(2.61)	(8.05)	(3.23)
Associate Professionals	10,507	2,305	19,675	3,840	27,519	5,725
	(14.48)	(5.19)	(20.18)	(8.78)	(24.07)	(12.77)
Craft and Related Workers	9,202	8,674	8,114	6,735	7,228	5,649
	(12.68)	(19.52)	(8.32)	(15.40)	(6.32)	(12.60)
Plant and Machine Operators	8,952	7,566	7,105	3,990	6,982	2,586
	(12.34)	(17.03)	(7.29)	(9.12)	(6.11)	(5.77)
Clerks	16,519	3,682	20,471	4,719	23,192	6,105
	(22.77)	(8.29)	(21.00)	(10.79)	(20.29)	(13.62)
Service and Shop Sale Workers	10,421	5,793	14,938	7,711	17,142	10,242
	(14.36)	(13.04)	(15.32)	(17.63)	(15.00)	(22.85)
Elementary Occupations	7,258	11,184	9,290	11,077	9,935	9,900
	(10.00)	(25.17)	(9.53)	(25.33)	(8.69)	(22.09)

Note: numbers in parentheses are percentages of respective labor force.

[13] After estimating the mean earnings of each occupation, individuals in the first two occupations get paid significantly higher than individuals with other occupations, and individuals with elementary occupation earn the least.

Some of the facts from Table 8 need to be documented. First, similar percentages of labor force for both natives and Chinese immigrants were engaged in the high-paid occupations in 1991. It implies that if Chinese immigrants were paid the same as natives, then we should observe no or little earnings gap at the upper percentiles. The fact is that the group earnings differential at the upper percentiles was present and the covariates differences do not account for the corresponding gap. Apparently, the difference in personal characteristics is not a major driver of the group earnings differential at the same percentiles in 1991. Instead, the earnings gap is mostly due to the difference in the returns to skills.

Second, the percentage of the labor force engaging in high-paid occupations for the Chinese immigrants had remained quite stable over time. For natives, the number rose rapidly from 12.97% in 1991 to 18.10 in 2001 and then it increased slightly to 19.45% in 2011. Apparently, the large difference in the labor force participation in the high-paid jobs between natives and Chinese immigrants had widened the group earnings differential over time. Put in another way, occupational segregation played an important role in shaping the earnings differential between natives and immigrants at the upper percentiles. This is consistent with the discussion above.

Third, more than 20% of the Chinese immigrant labor force were engaged in the low-paid occupations in each year. In contrast, natives only were 10% or less of the labor force taking low-paid jobs. Thus, a big portion of the earnings gap at the bottom of the distribution may be accounted for by occupation differences. In general, the Chinese immigrants engaging in low-paid occupations are poorly educated [14]. For example, in 1991, the average of those people did not even finish their primary school. Possibly, most of those Chinese immigrants were illegal immigrants who migrated to Hong Kong for economic reasons.

[14] There is no significant difference between males and females among the Chinese immigrants in terms of years of schooling.

Chapter 6

CONCLUSION

The main goal of this study is to examine three features of earnings in Hong Kong: earnings inequality and its underlying sources; gender earnings gap; and earnings differences between immigrants and natives. Throughout the study, the datasets used are the 5% samples of the 5 population census and by-census datasets over the period from 1991 to 2011. As a matter of fact, overall income inequality of Hong Kong had stayed at a very high level since 1991, and it increased moderately over the past two decades. The gender earnings gap widened only slightly during the same period, while the mean earnings difference between natives and Chinese immigrants grew substantially from 0.214 to 0.349 log points

To empirically investigate the determinants of overall inequality in Hong Kong, I performed a decomposition approach to examine the sources to the changes in overall inequality. Specifically, I estimated the effects of changes in the price of skills, changes in the distribution of skills, and changes in the distribution of the residuals on the changes in earnings inequality, separately. Surprisingly, the result of this study is not consistent with most of the previous studies in which a large portion of the changes in overall earnings inequality are due to unobservable characteristics. In this study, I found that a significant portion of the changes in earnings inequality can be attributed to the changes in observed individual characteristics and the changes in return to skills. More importantly, the rising skill prices, which is due to a significant demand shift from low-skilled workers to high-skilled workers in the economic restructuring process in Hong Kong, can account for a significant portion of the changes in income inequality. The composition effect plays an important role in explaining the residual inequality through a variance decomposition analysis.

For the studies of gender earnings gap and earnings differential between natives and immigrants, I applied the well-known Oaxaca-Blinder decomposition method to investigate the determinants of income disparity at the mean level. I found that more than one third of the gender earnings differential could be explained by the differences in personal characteristics in each year. This finding contradicts many of the previous studies which claimed that a substantial portion of the gender earnings gap in Hong Kong could not be explained by the covariates differences. Additionally, occupation difference accounts for a big part of the explained portion of the gender earnings differential. I obtained similar results when studying the earnings difference between natives and Chinese immigrants.

I also applied the Recentered Influence Function method to examine the earnings gap at other percentiles of the earnings distribution. At the upper percentiles, the gender earnings gap is relatively small, and most of the gap are accounted for by the composition effect, especially the occupational segregation. Over time the gap converged, and this is mainly due to a substantial rise in the female labor force participation in those high-paid, high-status jobs which used to be dominated by males. Higher educational attainment enables women to enter those prestigious occupations and apparently occupational upgrading contributes to the reduction in the gender earnings gap at the upper percentiles. At the lower percentiles, the gender earnings gap is relatively large, and over time it diverged substantially. Moreover, most of the gap is due to the differences in the skill prices between males and females.

On one hand, a lot more female workers have engaged in the elementary occupations, and a lot of the female workers doing low-paid, low-status jobs are older and less-educated women who had lost their jobs in the process of economic restructuring. On the other hand, male workers doing the same type of jobs on average are more experienced. Certainly, strong evidence shows that women at the bottom of the earnings distribution are greatly disadvantaged.

I obtained slightly different results for the earnings differential between natives and Chinese immigrants. Occupational segregation plays a crucial role in explaining the earnings gap for both the upper and lower percentiles. This finding implies that both “glass ceiling” and “glass floor” problems exist for Chinese immigrants in Hong Kong. For the highest-paid jobs, the labor force participation rate for natives grew rapidly over time while it remained quite stable for Chinese immigrants. For the lowest-paid jobs, the labor force participation for Chinese immigrants remained steady while it declined moderately for natives. Thus, the difference in the labor force participation rate between natives and Chinese immigrants for both the highest-paid and lowest-paid jobs has constrained the occupational mobility for Chinese immigrants. The most important reason for occupational segregation in Hong Kong is the difference in human capital, particularly education levels, between Chinese immigrants and natives. Chinese immigrants on average had received worse school training than natives in terms of both quantity and quality.

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Appendix A

ADDITIONAL RESULTS FOR CHAPTER 3

Table A1: Income Shares of Individuals from All Employment in Hong Kong, 1991-2011 (Three Times the Threshold)

year	Quintiles					Bottom 10%	Top 10%	Top 5%	Top 1%
	Q1	Q2	Q3	Q4	Q5				
1991	4.9	10.0	13.4	18.5	53.2	1.2	39.6	29.6	15.0
1996	4.8	9.2	12.4	17.8	55.9	1.6	42.5	32.5	17.6
2001	4.4	8.8	12.4	18.8	55.7	1.5	41.5	30.8	15.8
2006	4.3	8.6	12.2	18.7	56.2	1.5	41.6	30.6	15.5
2011	4.0	8.2	11.5	18.1	58.2	1.4	43.6	32.6	17.6

Note: the average income of the open-ended category is three times the threshold

Table A2: Income Shares of Individuals from All Employment in Hong Kong, 1991-2011 (Three Times the Threshold)

year	Quintiles					Bottom 10%	Top 10%	Top 5%	Top 1%
	Q1	Q2	Q3	Q4	Q5				
1991	4.7	9.7	13.1	18.0	54.5	1.2	41.3	31.6	17.4
1996	4.6	8.8	11.9	17.0	57.8	1.6	45.0	35.4	21.1
2001	4.2	8.4	11.9	18.0	57.5	1.5	43.7	33.5	19.1
2006	4.1	8.3	11.8	18.0	57.8	1.5	43.7	33.2	18.6
2011	3.8	7.8	11.0	17.2	60.3	1.3	46.3	35.9	21.7

Note: the average income of the open-ended category is four times the threshold

Table A3: Pooled and Single Regressions Results from Decomposition Approach in Hong Kong, 1991-2011, 1991-2001, 2001-2011

	1991-2011			1991-2001			2001-2011		
	Pooled Regression	1991 Only	2011 Only	Pooled Regression	1991 Only	2001 Only	Pooled Regression	2001 Only	2011 Only
Male	0.260	0.277	0.223	0.255	0.277	0.243	0.245	0.243	0.223
Educ	0.117	0.096	0.135	0.108	0.096	0.117	0.120	0.117	0.135
Exp	0.049	0.042	0.053	0.045	0.042	0.049	0.052	0.049	0.053
Expsq	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
Dur_HK	0.001	0.016	0.012	0.014	0.016	0.012	0.011	0.012	0.012

Note: all parameters are 1% level significant.

Table A4: Pooled and Single Regressions Results from Decomposition Approach in Hong Kong, 1991-2011, 1991-2001, 2001-2011 (Three Times the Threshold)

	1991-2011			1991-2001			2001-2011		
	Pooled Regression	1991 Only	2011 Only	Pooled Regression	1991 Only	2001 Only	Pooled Regression	2001 Only	2011 Only
Male	0.262	0.277	0.226	0.256	0.277	0.245	0.248	0.245	0.226
Educ	0.118	0.096	0.137	0.109	0.096	0.118	0.121	0.118	0.137
Exp	0.049	0.043	0.054	0.046	0.043	0.049	0.052	0.049	0.054
Expsq	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
Dur_HK	0.001	0.016	0.012	0.014	0.016	0.012	0.010	0.012	0.012

Note: all parameters are 1% level significant.

Table A5: Observable and Unobservable Components of Changes in Inequality in Hong Kong (Three Times the Threshold)

Differential	Total change (1)	Observed Quantities (2)	Observed Prices (3)	Unobserved Price And Quantities (3)
		A. 1991-2011		
90/10	0.094	0.028	0.044	0.023
90/50	0.028	0.003	0.016	0.009
50/10	0.057	0.022	0.023	0.012
		B. 1991-2001		
90/10	0.058	0.022	0.024	0.011
90/50	0.018	0.001	0.011	0.006
50/10	0.035	0.019	0.011	0.005
		C. 2001-2011		
90/10	0.036	0.009	0.020	0.008
90/50	0.011	0.001	0.009	0.001
50/10	0.022	0.008	0.009	0.006

Source: The Census and Statistics Department of Hong Kong, 1991-2011, compiled

Table A6: Within-Group Variance of Income by Experience-Education Cell in Hong Kong, 1991 and 2011

	within-group variance			work-force share		
	1991	2011	Change	1991	2011	Change
	(1)	(2)	(3)	(4)	(5)	(6)
A. *by education and experience*						
Primary and below						
exp<=10	0.1967	0.2688	0.0721	0.0028	0.0003	-0.0024
10<exp<=20	0.2069	0.1844	-0.0224	0.0319	0.0050	-0.0269
20<exp<=30	0.2573	0.3413	0.0840	0.0788	0.0111	-0.0678
30<exp	0.2503	0.2996	0.0493	0.1562	0.0993	-0.0569
Lower Secondary						
exp<=10	0.1657	0.2653	0.0996	0.0483	0.0104	-0.0379
10<exp<=20	0.2228	0.2030	-0.0197	0.0746	0.0326	-0.0420
20<exp<=30	0.2617	0.2848	0.0231	0.0573	0.0496	-0.0077
30<exp	0.3007	0.3207	0.0200	0.0324	0.0873	0.0549
Upper Secondary						
exp<=10	0.1505	0.2487	0.0982	0.1553	0.0709	-0.0844
10<exp<=20	0.2722	0.2356	-0.0366	0.1324	0.0936	-0.0388
20<exp<=30	0.4263	0.3944	-0.0319	0.0586	0.1028	0.0442
30<exp	0.5177	0.4960	-0.0216	0.0263	0.0943	0.0679
Post-secondary						
exp<=10	0.3421	0.3740	0.0320	0.0688	0.1424	0.0736
10<exp<=20	0.5811	0.5352	-0.0459	0.0423	0.1043	0.0620
20<exp<=30	0.8147	0.6461	-0.1687	0.0210	0.0691	0.0481
30<exp	0.8431	0.8453	0.0022	0.0131	0.0272	0.0142

Table A6 continued.

B. *weighted average (using alternative shares)*			
Actual shares	0.2901	0.3897	0.0996
1991 shares	0.2901	0.3140	0.0238

Appendix B

ADDITIONAL RESULTS FOR CHAPTER 4

Table B1: Overall Earning Trends in Hong Kong with Alternative Measures, 1991-2011

	1991	1996	2001	2006	2011
Mean Log Male Earning	9.299	9.458	9.632	9.586	9.619
	(0.696)	(0.753)	(0.775)	(0.803)	(0.831)
Mean Log Female Earning	8.957	9.143	9.244	9.233	9.220
	(0.649)	(0.721)	(0.783)	(0.817)	(0.870)
Mean Difference	0.342	0.315	0.388	0.353	0.398
Gender Earnings Ratio	71.0	73.0	67.9	70.3	67.2
Position of Mean Female in the Male Distribution	28.4	33.5	29.9	32.5	36.3

Note: numbers in parentheses are standard deviations

Table B2: Oaxaca-Blinder Decomposition Estimates in Hong Kong, 1991-2011

	1991		1996		2001		2006		2011	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
A. Parameters										
Education	0.043*	0.048*	0.049*	0.055*	0.052*	0.057*	0.054*	0.055*	0.055*	0.057*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience	0.046*	0.023*	0.043*	0.023*	0.050*	0.031*	0.055*	0.040*	0.047*	0.034*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Experience Squared	-0.001*	0.000*	-0.001*	0.000*	-0.001*	0.000*	-0.001*	-0.001*	-0.001*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Duration in Hong Kong	0.009*	0.008*	0.001*	0.000*	0.002*	0.009*	0.001	0.007*	-0.002*	0.009*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
B. Earnings Gap										
Overall	0.341		0.313		0.385		0.351		0.395	
Explained	0.113		0.124		0.173		0.162		0.168	
Unexplained	0.228		0.189		0.212		0.189		0.227	
% Exp.	33.19		39.53		44.86		46.05		42.44	

Note: numbers in parentheses are standard errors of estimates. All estimate parameters with asterisk (*) are significant at 95% confidence level.

Table B3: Kernel Estimate of Gender Earnings Gap at Selected Percentiles in Hong Kong with Multiple Bandwidth Choices for Females, 2001 and 2011

	10^{th}	50^{th}	90^{th}
Panel A. 2001			
Raw Earnings Gap	0.492	0.288	0.288
h=0.100	0.523	0.376	0.283
*h**=0.076	0.513[0.158]	0.376[0.187]	0.283[0.320]
h=0.038	0.497	0.383	0.283
***h*=0.030**	0.492[0.158]	0.383[0.187]	0.283[0.320]
h=0.001	0.466	0.351	0.285
Panel B. 2011			
Raw Earnings Gap	0.671	0.300	0.316
h=0.100	0.600	0.402	0.319
*h**=0.080	0.612[0.152]	0.398[0.188]	0.319[0.155]
h=0.040	0.639	0.382	0.319
h=0.010	0.665	0.330	0.319
***h*=0.001**	0.676[0.152]	0.305[0.188]	0.319[0.155]

Note: h* is obtained by applying $h^*=0.9AN^{-1/5}$. Optimal bandwidth choices are highlighted, and numbers in bracket represent the portion of the earnings gap being explained by the covariate difference.

Appendix C

ADDITIONAL RESULTS FOR CHAPTER 5

Table C1: Overall Earnings Trends for Natives and All Immigrants in Hong Kong, 1991-2011

	1991		1996		2001		2006		2011	
	Natives	All	Natives	All	Natives	All	Natives	All	Natives	All
Panel A. Overall										
Mean Earnings	9.245	9.054	9.435	9.160	9.596	9.214	9.555	9.147	9.585	9.104
Std. Dev	0.660	0.728	0.695	0.796	0.748	0.822	0.784	0.832	0.807	0.888
N	72,553	52,250	88,966	57,905	97,481	58,347	107,276	56,683	114,313	64,101
Mean Difference	0.191		0.275		0.381		0.408		0.481	
Panel B. Male										
Mean Earnings	9.352	9.221	9.509	9.366	9.681	9.523	9.620	9.483	9.643	9.519
Std. Dev	0.667	0.715	0.708	0.784	0.746	0.786	0.789	0.804	0.800	0.862
N	42,996	34,623	52,893	35,017	55,552	30,751	60,390	26,912	63,761	27,328
Mean Difference	0.130		0.143		0.158		0.136		0.124	
Panel C. Female										
Mean Earnings	9.089	8.724	9.326	8.845	9.482	8.870	9.471	8.843	9.512	8.796
Std. Dev	0.619	0.634	0.660	0.706	0.726	0.717	0.769	0.735	0.811	0.774
N	29,557	17,627	36,073	22,888	41,929	27,596	46,886	29,771	50,552	36,773
Mean Difference	0.364		0.480		0.612		0.628		0.716	

Source: Census and By-census datasets, compiled

Table C2: The Earnings Differential between Natives and All Immigrants in Hong Kong by Distribution Percentiles, 1991-2011

	Percentile								
	10th	20th	30th	40th	50th	60th	70th	80th	90th
1991	0.182	0.288	0.251	0.223	0.182	0.185	0.208	0.223	0.095
1996	0.383	0.464	0.339	0.251	0.223	0.274	0.310	0.193	0.201
2001	0.492	0.629	0.457	0.357	0.345	0.405	0.405	0.374	0.278
2006	0.455	0.687	0.531	0.478	0.427	0.442	0.435	0.348	0.330
2011	0.596	0.760	0.592	0.496	0.499	0.493	0.511	0.542	0.308

Note: The earnings gap is the log of earnings of natives at a certain decile minus the log of earnings of all immigrants at the same decile.

Table C3: Oaxaca-Blinder Decomposition Estimates of Earnings Differential between Natives and Chinese Immigrants in Hong Kong, 1991-2011

	1991		1996		2001		2006		2011	
	Natives	I_CHN	Natives	I_CHN	Natives	I_CHN	Natives	I_CHN	Natives	I_CHN
A. Parameters										
Male	0.219	0.352	0.153	0.283	0.151	0.311	0.114	0.249	0.106	0.241
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)
Education	0.074	0.022	0.075	0.028	0.082	0.027	0.073	0.033	0.072	0.035
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience	0.053	0.025	0.047	0.021	0.055	0.026	0.060	0.033	0.053	0.031
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Experience Sq.	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B. Earnings Gap										
Overall	0.214		0.263		0.304		0.308		0.349	
Explained	0.092		0.133		0.183		0.202		0.270	
Unexplained	0.121		0.1303		0.121		0.106		0.079	
% Exp.	43.23		50.54		60.21		65.47		77.39	

Note: numbers in parentheses are standard errors of estimates. All estimate parameters are significant at 95% confidence level.

Table C4: Summary of Oaxaca-Blinder Decomposition Method Estimates of Earnings Differential between Natives and All Immigrants in Hong Kong, 1991-2011

	1991	1996	2001	2006	2011
Panel A. Earnings Differential					
Overall Gap	0.191	0.275	0.381	0.408	0.481
% Explained	33.14	41.76	50.09	62.49	65.81
Panel B. Contribution of Covariates Differences to Earnings Differential					
Education	0.150	0.104	0.104	0.123	0.128
	[78.51]	[37.86]	[27.27]	[30.11]	[26.55]
Experience	-0.163	-0.092	-0.092	-0.086	-0.048
	[-85.27]	[-33.63]	[-24.23]	[-21.03]	[-9.96]
Gender	-0.015	-0.002	-0.002	0.010	0.014
	[-8.02]	[-0.57]	[-0.41]	[2.47]	[2.89]
Occupation	0.091	0.105	0.145	0.208	0.223
	[47.92]	[38.10]	[38.00]	[50.94]	[46.32]

Note: Each main entry of this table represents the contribution of each characteristic to the overall gap. Its percentage is in brackets.

Table C5: Kernel Estimate of Earnings Differential between Natives and Chinese Immigrants at Selected Percentiles in Hong Kong with Multiple Bandwidth Choices, 1991, 2001 and 2011

	10^{th}	50^{th}	90^{th}
Panel A. 1991			
Raw Earnings Gap	0.182	0.182	0.318
h_c=0.083, h_n*=0.051	0.245	0.174	0.325
h_c*=0.055, h_n*=0.051	0.244[0.192]	0.176[0.077]	0.324[-0.000]
h_c=0.028, h_n*=0.051	0.228	0.180	0.322
h_c=0.007, h_n*=0.051	0.183[0.192]	0.188[0.077]	0.319[-0.000]
h_c=0.004, h_n*=0.051	0.175	0.190	0.319
Panel B. 2001			
Raw Earnings Gap	0.288	0.234	0.405
h_i*=0.062, h_n=0.090	0.193	0.283	0.416
h_i*=0.062, h_n*=0.060	0.193[0.272]	0.283[0.206]	0.416[0.138]
h_i*=0.062, h_n=0.030	0.204	0.278	0.415
h_i*=0.062, h_n=0.015	0.230[0.126]	0.261[0.127]	0.415[0.235]
Panel C. 2011			
Raw Earnings Gap	0.262	0.357	0.470
h_c=0.120, h_n*=0.061	0.243	0.338	0.372
h_c*=0.060, h_n*=0.061	0.241[0.248]	0.338[0.268]	0.359[0.260]
h_c=0.030, h_n*=0.061	0.250	0.337	0.375
h_c=0.011, h_n*=0.061	0.262[0.248]	0.338[0.268]	0.425[0.260]
h_c=0.001, h_n*=0.061	0.270	0.338	0.372

Note: h* is obtained by applying $h^*=0.9AN^{-1/5}$. Optimal bandwidth choices are highlighted, and numbers in bracket represent the portion of the earnings gap being explained by the covariate difference.